The Short-Run Effect of Public Transit on Crime¹

PRELIMINARY AND INCOMPLETE: PLEASE DO NOT CITE WITHOUT PERMISSION

David C. Phillips Hope College

Danielle Sandler US Census Bureau²

Abstract

According to popular perception, public transit spreads crime. This belief is often a major reason for opposing expansion of urban mass transit systems. However, the existing empirical literature finds little evidence in support of this theory. We address this question using a novel identification strategy based on temporary, maintenance-related closures of stations in the Washington, DC rail transit system. The closures generate plausibly exogenous variation in transit access across space and time, allowing us to test the popular notion that crime can be facilitated by public transit. While we find no evidence that closing a rail station decreases crime at the closed station itself, we find strong evidence that closing stations reduces crime elsewhere. This reduction in crime is concentrated near stations and particularly at stations in neighborhoods where few previous offenders reside.

¹ We have received helpful comments from seminar participants at Hope College. We are grateful for help with data from the Office of Research and Analytical Services, DC Metropolitan Police Department. All remaining errors and omissions remain our responsibility.

² The research in this paper was undertaken prior to the author's employment at the US Census Bureau. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. The research in this paper does not use any confidential Census Bureau information.

1. Introduction

While many popular urban observers credit new rail lines with revitalizing urban areas and encouraging environmentally-friendly transportation (e.g. Yglesias, 2012), constructing new lines can be contentious. Ferguson (1994) describes an extreme situation in which a new light rail station in the community of Linthicum south of Baltimore led to a crime wave, subsequent police crackdown, and petitions to close the station. Anecdotes such as this provide popular fodder that may ultimately result in rail lines bypassing some affluent communities. The idea that public transit spreads crime is not limited to popular press and rumors. District of Columbia Metropolitan Police Chief Cathy Lanier has commented on both the tendency of crime to show up near public transit and its tendency to disappear when service is removed:

I can tell you the mobility factor is huge in terms of who your victims are and where they come from. And who your suspects, where they come from. And with mass transportation, if you look just at the way the metro lines run around the city, and I can tell you when the metro is down on the weekends for track work and certain lines are down I promise you my robberies go down. Every time they say track work, I'm good. (Lanier, et. al., 2013)

Clearly, both the general public and public safety experts support the idea that public transit can spread crime; however, scholarly support for this hypothesis is mixed at best. Geographic patterns of crime can reflect public transit routes (Block and Block, 2000), but this correlation may reflect factors other than the causal effect of access to public transit on crime. Studies aiming to isolate the effect of public transit on crime generally measure changes in crime occurring before and after construction of new rail stations. These studies generally find no increase in crime (Billings, Leland, and Swindell, 2011) or a redistribution of crime from affluent to low-income areas (Ihlanfeldt, 2003), which opposes the predictions of theoretical models based on the cost of committing crime. Using an identification strategy based on the extension of late night rail hours, Jackson and Owens (2011) find some effect of public transit when focusing on alcohol-related crime; however, they find only that public transit changes the composition of crime (fewer DUIs; more other alcohol-related crime) rather than the total amount.

From a public policy point of view, resolving the tension between the evidence and the popular belief that public transit spreads crime matters. If transit projects increase or redistribute crime, this should affect policing tactics and the cost-benefit calculus for new rail projects. With rail lines commonly criticized for high costs relative to other forms of public transit, large negative crime externalities might weigh against possible environmental or urban revitalization benefits. Of course, the existence of crime externalities does not immediately indicate that urban rail transport should be passed over, but it is one potentially important factor in measuring the net benefits of public transportation.

Our study contributes to the existing literature by investigating the effect of public transit on crime via a natural experiment in the Washington, DC metropolitan area. Over the past several years, the Washington Metropolitan Area Transit Authority (WMATA) has engaged in extensive renovation. As a result of the construction and maintenance work, various train stations in the WMATA system have been closed for a series of consecutive days for reasons unrelated to crime in the surrounding neighborhood. This provides a natural opportunity to exploit variation in train service across time and stations to measure the effect of transit service on crime in the vicinity of the train station.

Our use of maintenance-related station closures as a source of identification differs from the previous literature, which mainly focuses on permanent openings of new rail stations. This differentiates our estimates in two ways. First, station closures in our data are driven by maintenance needs. Maintenance needs are plausibly less related to surrounding neighborhood trends than the permanent placement of stations, making it less likely that our results will be biased. This provides an alternative source of identification that complements the existing literature. Second, the station closures we study last at most a few days. As a result, we measure the short-run effect of public transit on crime. Construction of new transit lines (e.g. Billings, Leland, and Swindell, 2011; Ihlanfeldt, 2003; Liggett, Loukaitou-Iseris, and Iseki, 2003) are relatively permanent policies with one-time temporal variation. This leads existing studies to generally estimate long-run effects over a period of several years. In the present study, we are able to estimate short-run effects of transit changes. While both are of interest, the short-run effect likely reflects a pure change in transit. As suggested by popular accounts (e.g. Ferguson, 1994), the long-run effect of transit on crime may include rational response by police, communities, and others to mitigate potential adverse effects; it also might induce changes in the distribution of residents, with those that value public transportation moving in. If measured long-run effects include these coping mechanisms, then transit may still generate a large, negative crime externality in the short-run and coping costs that should be considered in any cost-benefit analysis. Our data and natural experiment provide means to test this hypothesis.

Using this approach, we find strong support for the theory that public transit can spread crime. Consistent with the existing literature, we find no evidence that crime falls within ¹/₄ mile of a rail station when it is closed for maintenance. If anything crime increases slightly though this effect is statistically insignificant. However, we find that when a station is closed, crime falls at *other* stations. Stations on the same train line see crimes fall by 0.011 crimes per hour from a mean rate of 0.025 crimes per hour. We also find evidence that crime does not decrease in neighborhoods that tend to be the source of those committing crimes while the drop in crime is

concentrated in neighborhoods for which transit serves to import those committing crimes. Finally, we find no evidence that transit shutdowns simply disperse crime from near the station out into the neighborhood. If anything crime between ¼ and 1 mile from the stations also falls, though less than crime near the station. Altogether, these results match the main predictions of a simple model of rational criminal behavior where public transit lowers the opportunity cost of committing crimes and reducing access to public transit disrupts criminal behavior.

2. Illustrative Model

While the focus of this paper is empirical, a simple model can illustrate the different ways in which public transit may affect the decision to commit a crime. The model is a simple version of the Becker (1968) economic model of crime with a geographic dimension added in a manner similar to Ihlanfeldt (2003). Note that this model focuses on the interpretation of mass transit as a reduction in the opportunity cost of committing a crime, though other interpretations of our empirical results are plausible.

Consider a person *i* who lives at home location *h* and is deciding whether to work³, commit a crime in the home neighborhood, or commit a crime at another station *s*. If he works, he is paid an hourly wage $w_h \epsilon_i$, where w_h is the mean wage for workers from location *h*, and ϵ_i is an idiosyncratic component of the wage that varies from person to person and is non-negative. Rather than working, an individual can commit a crime at home or at location *s*. Committing the crime has an expected return (net of losses due to law enforcement) of v_h at home and v_s at the other station. Criminal activity requires *C* hours to commit the crime and t_{hs} hours to travel from home to the crime scene. We assume that the travel time is zero when committing a crime

³ We follow convention and assume that work is the alternative activity to committing a crime, but "work" could equally represent any activity other than crime that gives person i positive utility.

at home but positive when committing a crime elsewhere so that $t_{hh} = 0$ and $t_{hs} > 0$ when $s \neq h$.

The individual will commit a crime at the other station *s* if the return to crime at *s* is higher than both the return to working during the time it takes to commit the crime and also the return to committing a crime at home:

$$v_s \ge (C + t_{hs})w_h\epsilon_i$$
 and $v_s - (C + t_{hs})w_h\epsilon_i \ge v_h - Cw_h\epsilon_i$

More succinctly, a crime will be committed at location *s* if:

$$\epsilon_i \le \min\left\{\frac{v_s - v_h}{t_{hs}w_h}, \frac{v_s}{(C + t_{hs})w_h}\right\}$$
(1)

Similarly, he will commit the crime at home if it provides higher return than either working or committing the crime at location *s*. This simplifies to:

$$\frac{v_s - v_h}{t_{hs}w_i} \le \epsilon_i \le \frac{v_h}{Cw_h} \qquad (2)$$

Suppose that ϵ_i has distribution $F(\cdot)$ with density $f(\cdot)$. Then:

$$\Pr[Commit \ crime \ at \ other \ station \ s] = F\left[\min\left\{\frac{v_s - v_h}{t_{hs}w_h}, \frac{v_s}{(C + t_{hs})w_h}\right\}\right]$$
$$\Pr[Commit \ crime \ at \ home \ station] = F\left[\frac{v_h}{Cw_h}\right] - F\left[\frac{v_s - v_h}{t_{hs}w_i}\right]$$

The effect of cutting off access to public transit can be captured by increasing the travel time from one location to another, t_{hs} . As long as the derivatives are well-defined:

$$\frac{\partial \Pr[Crime \text{ at other}]}{\partial t_{hs}} \le 0$$
$$\frac{\partial \Pr[Crime \text{ at home}]}{\partial t_{hs}} \ge 0$$

In other words, cutting off public transit at home station h increases crime committed at home but decreases crime committed elsewhere. On the other hand, if a transit closure happened elsewhere, that would increase locally generated crime at that station but reduce it at station h. More generally, suppose that the world consists only of two stations with people making the same decision. Suppose that the number of people at station h considering committing a crime is N_h and the number of people at station s considering crime is N_s . Then, the amount of crime at station h, C_h , will be:

 $C_h = N_s * \Pr[Commit crime at other station] + N_h * \Pr[Commit crime at home]$

Thus, a station closure will have an ambiguous effect on total crime at any station because of the countervailing effects on locally generated crime and crime imported through the transit system:

$$\frac{\partial C_h}{\partial t_{hs}} = N_s * \frac{\partial \Pr[Crime \ at \ other]}{\partial t_{hs}} + N_h * \frac{\partial \Pr[Crime \ at \ home]}{\partial t_{hs}}$$

These theoretical results generate several implications that are important for the empirical exercises to follow:

- Closing a public transit station at a location has two countervailing effects on crime at that location: decreasing access from outsiders who wish to commit crimes but also "trapping" locals who wish to commit crimes elsewhere, who now commit local crimes
- Which of these two effects dominates depends in part on whether a station tends to export or import crime. If the closed station has a large population of potential criminals (large N_h), then a reduction in public transit may increase crime at that station. However, if a reduction in public transit access cuts off the station from others with large numbers of potential criminals (large N_h) then the transit closure may lower crime at that station
- Closing a public transit station at one location potentially affects all connected stations; even an ideal experiment with station closures would result in spillovers across connected stations

While our illustrative model focuses on the behavior of perpetrators, station closures may also affect the behavior of potential victims in similar ways. Closing station h may prevent individuals from station h from leaving, increasing the population of potential victims. On the other hand, nearby stations closing could prevent potential victims from arriving, decreasing crime. Finally, station closures may simply cause potential victims to be less concentrated, lowering opportunities for crime. In the empirical work that follows, we will necessarily be measuring the total effect of station closures, taking into account effects on both perpetrator and victim behavior.

3. Data

3.1. Crime Data

The main analysis makes use of daily, geo-coded crime data made available by the Washington Metropolitan Police Department. This data is publicly available at crimemap.dc.gov and data.dc.gov. We use data for all crimes committed in the District of Columbia from January 1, 2011 to October 7, 2013. Importantly, each crime lists not only the date, time, and type of crime but also its geo-coded block location. We drop homicides from our dataset because they do not include time of day. We combine the crime data with geo-coded locations of transit stations made available by WMATA to measure crime in the neighborhood of each station. For each day, *t*; hour, *h*; and station, *i*, in the sample we measure the number of crimes committed within ¹/₄ mile of the station. So, Y_{ithr} is the number of crimes committed on day *t* during hour *h* within *r* miles of station *i*. Our dependent variable in most specifications is $Y_{ithr_4^{-1}}$. For some specifications, however, we also make use of "rings" around each station of various radii. For instance, we define the half-mile ring around a station as the number of crimes occurring between ¹/₄ and ¹/₂ mile from the station:

$$C_{ith\frac{1}{2}} = Y_{ith\frac{1}{2}} - Y_{ith\frac{1}{4}}$$

The data also includes information on the type of crime. We designate assault and sexual assault as violent crimes. We designate robbery, arson, burglary, stolen auto, theft and theft from auto as property crimes.

Table 1 provides summary statistics. The first column lists the summary statistics for the full sample period. On an average day, there are 0.025 crimes within ¼ mile of the average station in a typical hour. Property crimes account for 95% of all crimes near rail stations. An average of 0.052 crimes occur every hour between ¼ and ½ mile and 0.191 crimes between ½ and 1 mile. Re-scaled to account for the fact that a larger radius leads to a larger land area, the density of crimes per sq. mi. falls as one travels outward from 0.127 to 0.088 to 0.022 for these concentric rings.

3.2. Station Closure Data

We combine the crime data with a novel dataset on maintenance-motivated station closures and delays in the Washington Metropolitan Area Transit Authority (WMATA) rail system. We code the station and timing of the closures directly from WMATA news releases from the organization's website, <u>www.wmata.com</u>. Our data currently includes 4,897 stationhour closures. The vast majority of these have occurred since 2011 when WMATA began a large-scale maintenance program on the rail system. While this maintenance program has included several components (delays, single-tracking, etc.), we focus solely on instances in which rail access to a station is completely eliminated and replaced by shuttle buses. We do this because closures generate significant delays, often a half hour or more, in reaching a destination. Importantly, these closures are motivated solely by maintenance needs, a factor which should be unrelated to crime levels. Given the conclusions from the theoretical model, we measure treatment as not only the closure of a particular station by also closures of connected stations. To start, define T_{ithl} as whether maintenance shut down line l of station i for any part of hour h on day t. There are four rail lines in our data (Red, Orange, Blue, and Green).⁴ We use this basic data to compute four separate treatment variables. First, we measure the extent to which an individual station was closed:

$$T_{ith} = \frac{1}{L_i} \sum_{l} T_{ithl}$$

where L_i is the number of lines travelling through station *i*. Thus, T_{ith} equals 1 if all lines are closed in station *i* for at least part of hour *h* of day *t*. Due to spillover effects of the closure of one station on crime at another station, we will also be interested in the extent of closures within the whole rail system:

$$\bar{T}_{(i)th} = \frac{1}{I-1} \sum_{j \neq i} T_{jth}$$

where *I* is the number of stations in the system. $\overline{T}_{(i)th}$ measures the fraction of the entire system, other than station *i*, that is closed on day *t*. Finally, since spillovers of crime are most likely to affect directly connected stations, we also measure the fraction of stations on the same line(s) as station *i* that are closed. Similarly, we can measure the proportion of the system not directly connected to *i* that is closed.

As demonstrated in the first column of Table 1, these 4,897 station-hours of closures are a small fraction of the sample, representing about 0.4% of all station-line-hours. The remaining columns of Table 1 provide some descriptive comparisons of the crime and closure data. The

⁴ As of this writing, a Silver line is also under construction. There is also a Yellow line in operation, though within the District of Columbia, it follows the same path as the Green line, only diverging after leaving DC for Virginia. Thus, we consider the Green and Yellow lines to be identical.

second and third column compare days on which no stations are closed to days on which at least one station is closed. By definition, the fraction of stations closed in column two is zero. The third column demonstrates that when at least one station is closed, about 6% of the system tends to be closed, which is equivalent to about 3 out of the 42 stations. Also of note is that 92% of closures occur on weekends or holidays. Clearly, WMATA targets station closures for these low-ridership times and controlling for this fact will be important in our analysis. In fact, this is probably why crime is higher on days with station closures vs. those without. The final two columns of Table 1 provide a comparison of closed versus open stations on days in which some closures occur. Crime near stations is lower when stations are closed (0.021 vs. 0.027 crimes) though this, of course, does not control for selective choice of stations. When stations are closed, they are typically fully closed, with 92% of their lines closed. Finally, if other stations are closed, they tend to be ones on the same lines. When a given station closes, 12% of the rest of the lines connected to the station tend to close.

3.3. Complementary Data Sources

We use a small number of complementary data sources. As the theory above indicates, station closures may have heterogeneous effects depending on the tendency of a particular location to be a source or a destination for those committing crimes. We measure the tendency of a location to be a source for criminals by measuring the fraction of the population that is under correctional supervision (e.g. on parole). For each police service area (PSA), we calculate the fraction of the population under correctional supervision using May 2013 data from the DC Court Services and Offender Supervisory Agency (CSOSA, 2013) and estimates of PSA population as calculated by NeighborhoodInfo DC (a partnership involving the Urban Institute) using Census population counts. Since the parts of the quarter-mile radius circle around a given

train station may be in multiple PSAs, we assign a weighted average to the station based on the fraction of crimes committed in each PSA during 2012. In summary, we calculate the fraction of the population near each station that is under court supervision and use this as a measure of the tendency of a train station to be a source of those committing crimes. Table 1 shows that an average station will have 2% of its resident population under court supervision and stations with greater supervised populations are slightly more likely to be shut down.

Finally, at times we control for whether the day in question is a holiday or a weekend. We code this variable as an indicator for days on which there is no S&P 500 listing.

4. Identification Strategy

4.1. Station Closures

The correlation between public transit access and crime is widely reported by popular press (Ferguson 1994) and law enforcement (Lanier, et. al. 2013). As discussed above, a large literature examines the topic as well. Of course, the location of transit stations may be correlated with pre-existing crime patterns or other related factors, obscuring the actual causal effect. Transit stations may be placed in more populated or higher income areas due to higher potential ridership, or they may be placed in high poverty areas as part of urban renewal projects. A few studies explicitly attempt to identify the causal effect of transit on crime via natural experiments. Ihlanfeldt (2003) and Billings, Leland, and Swindwell (2011) use a long-run, fixed effects approach that measures the change in crime when new transit stations are opened. Contrary to conventional wisdom, the most careful existing studies find at most a small increase in crime when new transit stations open. A fixed effects identification strategy based on construction of new stations alleviates some bias resulting from endogenous placement of stations. However, bias will still exist if stations are placed in "up-and-coming" neighborhoods with falling crime

trends, though differentiating between the announcement and opening of a station using highfrequency data can alleviate this bias to some extent (Billings, Leland, and Swindell, 2011). While a significant improvement, even separating the announcement of new stations from their opening may confound the effect of transit with the effect of other changes that may occur in the neighborhood as a result of the opening of a transit line, such as investment or migration to and from the area.

In the present study, we continue the trend toward measuring the effect of public transit on crime using natural experiments; however, we diverge from the existing literature in that we intentionally focus on short-term changes in transit service that are determined by necessary track maintenance. In particular, we study the time period from 2011-2013 during which the Washington Metropolitan Area Transit Authority conducted extensive track maintenance that required fully shutting down rail stations and replacing the trains with buses, leading to extensive delays. We use these station closures as a natural experiment to examine whether shutting down access to public transit affects crime patterns near transit stations in Washington, DC.

Our approach differs from the previous literature in two main ways. First, by using variation in public transit access caused by the location of maintenance needs rather than locations selected for new construction, we generate results that result from a complementary method of identification and are less likely to be biased. Our approach is most similar to Jackson and Owens (2011), who study whether extending evening hours for the DC public rail system affected alcohol-related crimes. Focusing on changes in service where crime is less likely to be taken into account by decision makers provides a strong *ex ante* case that an unbiased causal effect can be measured. Second, we measure a short-term rather than long-term effect of public transit on crime. As noted in other studies, the long-run effect of public transit on crime in a

neighborhood may include not only the tendency of public transit to transport those committing crimes, but also changes in home values, neighborhood composition, and policing. By exploiting a short-run change in public transit access, we are able to measure whether public transit affects crime in the short run, absent these general equilibrium effects. This is particularly useful given the overriding null result of the literature. We can test whether public transit spreads crime in the short run in a setting where these long-term positive influences are constant. Of course, our measured effect of public transit may still include multiple effects, since transit closures will both lower the opportunity cost of committing crime far from home (as emphasized in the model above) and change in the distribution of potential victims at one location. However, we can test cleanly whether public transit access affects crime rates in the short-run.

4.2. Effect of a Station Closure on Own Neighborhood

To start, we analyze the impact of a station closure on crime in the neighborhood immediately surrounding it. We use a fixed effects approach to compare changes in crime at a station where a maintenance-related closure occurs to other stations where the station remains open. This can be analyzed using the equation:

$$C_{ith} = \alpha + \beta T_{ith} + \delta X_{th} + \eta_i + \epsilon_{it} \qquad (3)$$

where C_{ith} is the number of crimes within one quarter mile of station *i* on date *t* and hour *h*; T_{ith} is the fraction of station *i*'s line that are closed on day *t* and hour *h*; X_{th} is a vector of date and hour controls; η_i is a station fixed effect; and ϵ_{it} is an error term. Our preferred specification will include fixed effects for the day of the week interacted with the hour of the day, fixed effects for month interacted with year, and a dummy for holidays and weekends. In this equation, the estimate for β identifies the average treatment effect of closing a transit station on crime at the same station. The effect is cleanly identified using variation in transit availability generated by

unrelated maintenance issues with the rail system while controlling for fixed individual station characteristics and natural variation in crime over time.

This strategy measures the short-run effect of transit on crime by comparing changes in crime at stations that WMATA shuts down to that station's typical weekly crime trend and to stations that do not shut down. The fixed effects for station and the date controls alleviate concerns regarding whether station shutdowns are planned for stations with higher crime (e.g. higher volume stations) or dates/hours with lower crime (e.g. weekends). When using this strategy, we assume that crime at stations remaining open is not affected by closures and that stations are not chosen to be closed on days in which they would otherwise have high/low crime relative to other stations. The latter assumption is plausible and represents a strength of this identification strategy based on maintenance-related closures.

4.3. Effect of a Station Closure Across the Entire Rail System

However, the conclusions of our theoretical model indicate that stations remaining open may, in fact, be affected by transit closures. For instance, a station closure in a neighborhood where residents have a higher propensity to commit crimes might lower crime in other neighborhoods connected to that station by mass transit. In the extreme, a closure at one crucial station may affect all other stations in the system because closing one station delays people travelling not only to and from that station but also through that station on the way to other destinations.

As such, theory indicates we should test for whether having connected stations shut down affects crime rates. We do this in two ways. First, we modify (3) to test if crime rates are related to the fraction of the entire train system (other than station i) that is closed:

$$C_{ith} = \alpha + \beta T_{ith} + \gamma T_{(i)th} + \delta X_{th} + \eta_i + \epsilon_{it} \qquad (4)$$

In this setup, γ measures whether crime rates respond to the fraction of other stations that are shut down, $\overline{T}_{(i)th}$. We expect that the effect of closures at other stations should depend on whether the two stations are closely connected. Thus, we can also test whether closures at other stations have a greater effect when the closed station and station *i* are on the same rail line:

$$C_{ith} = \alpha + \beta T_{ith} + \gamma_1 Same \overline{T}_{(i)th} + \gamma_2 Other \overline{T}_{(i)th} + \delta X_{th} + \eta_i + \epsilon_{it}$$
(5)

where $Same\overline{T}_{(i)th}$ is the fraction of stations that are closed on lines passing through *i*, and $Other\overline{T}_{(i)th}$ is the fraction of stations on other lines that are closed. We could expect a larger (negative) effect within the same line, i.e. $\gamma_1 < \gamma_2$.

The spillover effects of closing one station on crime at another station (γ coefficients in equations (4) and (5)) must be identified using variation over time. Since the hypothesis is that station closures may affect the whole system, including date-hour fixed effects is not possible. We instead control for time trends in a variety of different ways. In our preferred specification, we control for fixed effects for the day of the week interacted with the hour of the day, fixed effects for month interacted with year, and a dummy for holidays and weekends.

Thus, we assume that crime rates on the same hour and day of week are good proxies for the crime station *i* would have experienced if it had not had a closure.

4.4. Heterogeneous Effects

Even an unbiased average treatment effect may not fully characterize the effect of public transit on crime. The theory above specifically predicts that the effect will depend on various factors, particularly the size of the population of potential criminals residing at the station of interest relative to the same population at other connected stations. As above, we define the size of the population that resides at station i and is considering committing a crime as N_i . Then, the

regressions of interest would modify the above regression to include a term that interacts N_i with the treatment.

$$C_{ith} = \alpha + \beta_0 T_{ith} + \beta_1 T_{ith} * N_i + \delta X_{th} + \eta_i + \epsilon_{it} \quad (6)$$

$$C_{ith} = \alpha + \beta_0 T_{ith} + \beta_1 T_{ith} * N_i + \gamma_0 \overline{T}_{(i)th} + \gamma_1 \overline{T}_{(i)th} * N_i + \delta X_{th} + \eta_i + \epsilon_{it} \quad (7)$$

$$C_{ith} = \alpha + \beta_0 T_{ith} + \beta_1 T_{ith} * N_i + \gamma_0 Same \overline{T}_{(i)th} + \gamma_1 Same \overline{T}_{(i)th} * N_i + \gamma_2 Other \overline{T}_{(i)th} + \gamma_3 Other \overline{T}_{(i)th} * N_i + \delta X_{th} + \eta_i + \epsilon_{it} \quad (8)$$

From the theory above, we would expect the interaction term β_1 to be positive because if a station shuts down and has a large population of potential criminals, then we would expect crime to increase at that station. We would expect γ_1 to be positive also because if other stations shut down and station *i* is relatively more likely to be a source of perpetrators, then those individuals would have fewer outside targets, making them more likely to commit crime at home. Ideally, N_i would be measured directly using data on residential locations of those who commit crimes. We approximate this by measuring the fraction of the population near a given train station that are under court supervision.

5. Results

5.1. Own-Station Effects

We first estimate the effect of public transit station closures on crime using equation (1), i.e. by using an identification strategy that measures whether crime falls at stations closed for maintenance relative to stations remaining open. Table 2 reports the raw correlation between crime within a quarter mile of the station and the station closure variable. The coefficient of -0.004 indicates that closing the station for a full day is associated with 0.004 fewer crimes per hour (relative to a mean of 0.025). This is a meaningful decrease, though it is not statistically significant. Of course, this number is simply a correlation and does not have any meaningful

causal content. Columns 2 of Table 2 adds station fixed effects. Column 3 adds day of weekhour fixed effects, month-year fixed effects, and a holiday dummy. Column 4 adds date fixed effects. Regardless of the time controls, the estimate is actually positive, small and not statistically different from zero.

5.2. Spillover Effects

Table 3 investigates the possibility of spillover effects across stations in more detail using the identification strategy of equations (4) and (5). This method tests whether crime falls when other connected stations are closed. The first two columns of Table 4 do not distinguish between whether the closing station is near or far from the station at which crime is measured. The first column controls for trends in crime over the week and over the calendar while the second column adds date fixed effects. The coefficient in column 1 indicates that crime drops by 0.005 crimes per hour if the entire rest of the system is closed for maintenance. This is economically large, 20 percent of the mean hourly crime rate, but not statistically significant. The effect grows to a very large but imprecisely measured effect of -0.02 when controlling for date fixed effects in column 2. These results are imprecise but suggest that closing one station may reduce crime at another station.

The latter two columns of Table 3 test this hypothesis more narrowly, examining whether closing other stations on the same train line has a greater effect than closing stations on other lines. These results strongly support this idea, indicating that closing stations leads to large decreases in crime at other stations on the same line. The results of column 3 indicate that crime drops by a statistically significant 0.011 crimes per hour when maintenance closes down all other stations on the same line.⁵ This effect grows to a very large drop of 0.017 crimes per hour when

⁵ Of course, WMATA does not shut down all stations at once. The effect of shutting down one connected station would be much smaller. On the other hand, the shutdown of one station would affect multiple connected stations.

controlling for date fixed effects. However, minimal variation in closures within a day makes this measurement imprecise. On the other hand, when stations on other lines close the effect on crime is smaller and statistically insignificant. These results confirm match expectations of what would occur if public transit facilitates committing crimes. Closing a station reduces crime at other nearby stations but not at stations that are not directly connected to that station.

5.3. Heterogeneous Effects

The theory also predicts that closing stations should have heterogeneous effects. In particular, closing nearby stations should not reduce crime at stations that tend to be the home station for those committing crimes. If anything, cutting off potential targets should increase crime at these stations. On the other hand, reductions in crime should be concentrated at stations that are targets, i.e. stations that are a sink rather than a source for those committing crimes. We test this in Table 4 by interacting the treatment variables with a "baseline crime" variable that measures the percentage of the population under court supervision near that station. As shown in the first column, we continue to be unable to detect effects of the station closure on crime at that station. As shown in the second column, our results remain noisy when we examine spillovers across the entire system.

However, we find some evidence matching the predictions of theory when examining spillovers across stations on the same transit line. The positive coefficient of 0.006 on the interaction term in column 3 indicates that the drop in crime that results from station closures at nearby stations is greatest at stations that tend to be sources of those committing crimes and smallest at stations with a many such individuals. The coefficient of -0.0206 indicates that a station with no parolees living nearby would see a drop of .0206 crimes per hour if its entire line

As a result, another way to interpret this coefficient is as the total reduction in crime across all stations on a line when one station on that line is closed.

were shut down. However, a station with 4% of the nearby population under court supervision (1 s.d. above the mean) would have no predicted drop in crime (-0.0206 + 4 * 0.00552 = 0.00148). The marginal statistical significance of the interaction term prevents overly strong interpretation of these results. However, the measured effects are consistent with the prediction of theory.

5.4. Distance from the Station

We observe that crime falls when nearby stations are closed and particularly so at stations that are less likely to be sources of those committing crimes. The policy implications of these results, however, is difficult to determine without knowing whether public transit is really causing new crime or if it is simply concentrating all crime in the neighborhood in one location. To test this proposition, we replicate the above results for areas further than 1/4 mile from each station. Table 5 shows the results of this analysis. Columns 1 and 2 simply repeat earlier results showing that crime falls when stations on the same line are closed and that this effect is smaller in places with a large concentration of residences of individuals under court supervision. The second and third columns repeat the same econometric specification but simply change the dependent variable to be crimes committed between $\frac{1}{4}$ and $\frac{1}{2}$ mile from the train station. The coefficient on -0.016 indicates that crime falls by 0.016 crimes per hour if the rest of the train line is shut down. Between $\frac{1}{2}$ and 1 mile from the station, the decrease is 0.007 crimes per hour. Clearly, these results do not justify concerns that closures simply disperse crime further from the station. If anything, crime falls further away as well. The effects also decay with distance from the station, as one would expect. The outcomes are counts and the size of the area of land covered increases as the radius increases. Taking into account the increasing land area, crime drops by 0.056 crimes per sq. mi. within $\frac{1}{4}$ mile of the station, 0.027 crimes per sq. mi. between

¹/₄ and ¹/₂ mile, and 0.003 crimes per sq. mi. between ¹/₂ and 1 mile. The measured effects match a model of a real reduction in crime that is concentrated close to the station rather than simply reshuffling crime near and far from the station.

5.5. Types of Crime

TBD

6. Conclusion

We study the effect of public transit on crime using temporary, maintenance-related rail station closures in Washington, DC as a source of variation in public transit access. Closure of a rail station causes no measurable decrease in crime at the station itself. However, we find strong evidence that closing down stations reduces crime at other connected stations. We also find that crime falls little at stations that are home to many individuals under court supervision and much more at stations where there are few such individuals. Altogether, the results provide strong results supporting the idea that public transit can spread crime, leading to higher crime rates in more affluent neighborhoods.

References

Becker, G. (1968) "Crime and Punishment: An Economic Approach." *Journal of Political Economy*, 76(2).

Billings, S. (2011) "Estimating the Value of a New Transit Option." *Regional Science and Urban Economics*, 41.

Billings, S., S. Leland, and D. Swindell (2011) "The Effects of the Announcement and Opening of Light Rail Transit Stations on Neighborhood Crime." *Journal of Urban Affairs*, 33(5).

Block, R. and C.R. Block (2000) "The Bronx and Chicago: Street Robbery in the Environs of Rapid Transit Stations." in *Analyzing Crime Patterns: Frontiers of Practice*, ed. V. Goldsmith, et. al. SAGE Publications

CSOSA (2013) "First Police District Offender Profile." <u>http://www.csosa.gov/about/offender-profile.aspx</u> Accessed: 7/1/2013.

Ferguson, G. (1994) "Lock the House: Here Comes the Train." U.S. News and World Report, August, 7, 1994.

Ihlanfeldt, K. (2003) "Rail Transit and Neighborhood Crime: The Case of Atlanta, Georgia." *Southern Economic Journal*, 70(2).

Jackson, C.K. and E.G. Owens (2011) "One for the Road: Public Transportation, Alcohol Consumption, and Intoxicated Driving." *Journal of Public Economics*, 95.

Lanier, C., J. Lynch, J. Roman, and N. La Vigne (2013) "Putting Homicide Rates in Their Place." N. La Vigne (Chair). Symposium at the Urban Institute; March 5, 2013.

Liggett, R., A. Loukaitou-Iseris, and H. Iseki (2003) "Journeys to Crime: Assessing the Effects of a Light Rail Line on Crime in the Neighborhoods." *Journal of Public Transportation*, 6(3).

Yglesias, M. (2012) *The Rent is Too Damn High: What to Do About It, and Why It Matters More Than You Think.* Simon & Schuster: New York.

Table 1: Summary Statistics

	All	No Stations Closed	Any Station Closed All	Any Station Closed Closed Stations	Any Station Closed Not Closed Stations
Number of crimes:					
-All, zero to quarter mile	0.025	0.025	0.027	0.021	0.027
-All, quarter to half mile	0.052	0.052	0.056	0.043	0.057
-All, half to one mile	0.191	0.189	0.208	0.156	0.212
-Violent, zero to quarter mile	0.001	0.001	0.001	0.001	0.001
-Violent, quarter to half mile	0.003	0.003	0.004	0.003	0.004
-Violent, half to one mile	0.010	0.010	0.013	0.011	0.013
-Property, zero to quarter mile	0.024	0.024	0.025	0.020	0.026
-Property, quarter to half mile	0.050	0.049	0.053	0.039	0.053
-Property, half to one mile	0.180	0.179	0.195	0.146	0.065
Fraction of line-hours closed:					
Station	0.004	0.000	0.060	0.917	0.000
System	0.004	0.000	0.060	0.050	0.060
Own line(s)	0.004	0.000	0.058	0.124	0.054
Other lines	0.004	0.000	0.060	0.005	0.063
Holiday/weekend	0.31	0.26	0.92	0.91	0.92
Own crime	2.01	2.01	2.01	2.38	1.99
Sample size	1,019,088	943,740	75,348	4,897	70,451

Unit of observation is station-day-hour. Sample period covers January 1, 2011 - October 7, 2013. All listed quantities are means, except for the number of observations.

Table 2: Own-Station Effects

Dependent variable:

Number of Crimes within 1/4 Mile

	Raw Correlation	Station FEs	Station Fes	Both FEs
Fraction Station Classed	0.00207	0.00104	0.000017	0.00150
Fraction Station Closed	-0.00397	0.00194	0.000617	0.00159
	(0.00241)	(0.00242)	(0.00218)	(0.00193)
Holiday/Weekend				
Dummy		-0.00473***		
			(0.00146)	
Station FEs	No	Yes	Yes	Yes
Date FEs	No	No	No	Yes
DOW X Hour FE	No	No	Yes	Yes
Month X Year FE	No	No	Yes	No
Ν	1019004	1019004	1019004	126966

Unit of observation is station-date-hour. Standard errors in parentheses; *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. The dependent variable is the number crimes within 1/4 mile of the station. Standard errors are clustered at the station level. The final column restricts the sample to those days where at least one station is closed.

Table 3: Spillovers

Dependent variable: Number of Crimes within 1/4 Mile

	System- System-			
	Wide	Wide	Own Line	Own Line
Fraction Station Closed	0.000790	0.00114	0.00196	0.00224
	(0.00214)	(0.00199)	(0.00224)	(0.00200)
Fraction System Closed	-0.00534	-0.0212		
	(0.00931)	(0.0344)		
Holiday/Weekend Dummy	-0.00467***		-0.00465***	
	(0.00149)		(0.00148)	
Fraction of Line Closed			-0.0111**	-0.0174*
			(0.00553)	(0.00946)
Fraction of Other Lines				
Closed			0.00262	-0.00811
			(0.00793)	(0.0153)
Station FEs	Yes	Yes	Yes	Yes
DOW X Hour FEs	Yes	Yes	Yes	Yes
Month X Year FEs	Yes	No	Yes	No
Date FEs	No	Yes	No	Yes
Ν	1019004	126966	1019004	126966

Unit of observation is station-date-hour. Standard errors in parentheses; *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

The dependent variable is the number crimes within 1/4 mile of the station. Standard errors are clustered at the station level. The final column restricts the sample to those days where at least one station is closed.

Table 4: Heterogeneous Effects

Dependent variable: Number of Crimes within 1/4 Mile

	Own	System-	System-
	Station	Wide	Wide
Fraction Station Closed	0.00133	0.00149	0.00399
	(0.00444)	(0.00433)	(0.00445)
Baseline Crime*Fraction Station Closed	-0.000284	-0.000277	-0.00106
	(0.00115)	(0.00105)	(0.00106)
Fraction System Closed		-0.00524	
		(0.0105)	
Baseline Crime*Fraction System Closed		-0.0000414	
		(0.00529)	
Fraction of Line Closed			-0.0206***
			(0.00689)
Baseline Crime*Fraction Line Closed			0.00552*
			(0.00305)
Fraction of Other Lines Closed			0.0115
			(0.00991)
Baseline Crime*Fraction Other Line			
Closed			-0.00465
			(0.00383)
Station FEs	Yes	Yes	Yes
Date Controls	Yes	Yes	Yes
Ν	1019004	1019004	1019004

Unit of observation is station-date-hour. Standard errors in parentheses; *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. The dependent variable is the number crimes within 1/4 mile of the station. Standard errors are clustered at the station level. Date controls include DOWXhour FE, monthXyear FE, and a holliday-weekend dummy.

Table 5: Effects Across Space

Dependent variable: Number of Crimes within Different Radii

i

	Zero to	Zero to	Quarter to	Quarter to		
Distance from Station:	Quarter	Quarter	Half	Half	Half to Mile	Half to Mile
Fraction Station Closed	0.00196	0.00399	0.00341	0.00612	-0.000497	-0.00350
	(0.00224)	(0.00445)	(0.00301)	(0.00368)	(0.00623)	(0.0106)
Baseline Crime*Fraction Station Closed		-0.00106		-0.00121		0.000976
		(0.00106)		(0.00158)		(0.00287)
Fraction of Line Closed	-0.0111**	-0.0206***	-0.0162*	-0.0210*	-0.00754	-0.0177
	(0.00553)	(0.00689)	(0.00846)	(0.0121)	(0.0317)	(0.0505)
Baseline Crime*Fraction Line Closed		0.00552*		0.00286		0.00618
		(0.00305)		(0.00491)		(0.0177)
Fraction of Other Lines Closed	0.00262	0.0115	0.00262	0.0100	-0.00782	0.0774**
	(0.00793)	(0.00991)	(0.0116)	(0.0198)	(0.0233)	(0.0318)
Baseline Crime*Fraction Other Line Closed		-0.00465		-0.00383		-0.0437***
		(0.00383)		(0.00647)		(0.0106)
Station FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ν	1019004	1019004	1019004	1019004	1019004	1019004

Unit of observation is station-date-hour. Standard errors in parentheses; *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. The dependent variable is the number crimes within different radii of the station. Standard errors are clustered at the station level. Date controls include DOWXhour FE, monthXyear FE, and a holliday-weekend dummy.