Criminal Ram-page: The Impact of National Team Movements on Local Crime

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We develop a synthetic control that models a fictional St Louis in which the Rams, formally the NFL team for St Louis, never relocated to Los Angeles, as occurred in 2016. Using crime data From the FBI UCR Program and other demographic information we modeled an effective synthetic St Louis and found a significant decrease in crime in the years following the relocation.

Section I: Introduction

How closely associated are sports teams and crime? What effect does the presence of a NFL team have on a city's crime? Sports fans often exhibit an emotional response to the results of games, resulting in violence within the wider community. Many examples of extreme violence are observed in response to sports outside of the United States. Within the United States, ties between domestic violence and professional American football have been discovered, although the relationship is complicated. This includes a spike in domestic violence immediately after an unexpected loss of a home team (Card & Dahl, 2011). More than just the game results, simply hosting a game has been found to lead to increased crime in a city (Rees & Schnepel). The literature suggests that crime is a major cost to a city hosting a national sports team, but may not be considered by city leadership or franchise owners.

In 2016 the NFL St. Louis Rams moved from St. Louis, Missouri to Los Angeles, California after being in St. Louis since 1994. We examine the effect of this move on the crime rate in St. Louis by creating a synthetic St. Louis which retained the Rams. The remainder of this paper is structured as follows: Section II describes the data collected, section III discusses the empirical strategy, section IV examines our results and section V concludes.

Section II: Data

We use data collected by the various law enforcement agencies in each metropolitan area of the United States, which includes both city and county level data from 2006-2018. These data contain the total numbers of various types of crime: assault, burglery, theft, vehicle theft, robbery, homicide (including manslaughter), property crimes, rape, and violent crimes and their rates per 100,000 residents. Also included are the name of the county or municipality of occurrence, the related metropolitan area and their respective populations. These data are collected at the local level but are submitted to the Federal Bureau of Investigation through the National Incident-Based Reporting System as a means of uniform reporting and regulation of law enforcement. This is part of the Uniform Crime Reporting Program that distributes de-identified crime data freely as public records.

We merge the FBI data with data taken from the IPUMs USA which harmonizes census data with American Community Surveys. These data contain the sex, age, race, employment status, income, and education level for individuals as well as area of residence. We collapse these data to find rates for gender, age, race, unemployment, poverty, average income, high school completion, and those with some college education for each metropolitan area in the sample.

We analyze summary reports from each participating metropolitan area that gives totals and rates for a given year. Subcategory predictors are used to identify cities of similar criminal characteristics in synthesizing the control. We are most interested in knowing the effect on overall crime.

For best comparisons between cities, we are most concerned with the crime rate per crime type per 100,000 residents in a given metropolitan area. We match on the populations of the area and the other predictors to create a control from the cities that appear most similar to St. Louis to maintain an effective and representative counterfactual. Our data are effective in their ability to model the relevant features of each area, allowing us to use many donors and increasing the chance of an accurate synthetic control for St. Louis.

The weakness of our data is its variability in the reporting of crime and defining of metropolitan areas. Due to the freedom agencies possess in choosing to participate and submit data, as well as changes in the boundaries of a defined metropolitan area, there are some years that the crime or demographic data for St. Louis and other cities are not counted. We adjust for this by restricting the window to 2012-2018, during which all St. Louis data are available, which increases uniformity at the cost of 6 years of data. We further restrict our sample to only include metropolitan areas that have total crime reported for every year within this window, and areas in which some of both crime and demographic data are available for each year. After these restrictions there are 144 metropolitan areas left in our sample, including St. Louis.

Section III: Strategy

We use a synthetic control for comparative models as described in Abadie, Diamond, and Hainmueller (2010) that minimizes the root mean prediction error loss function (RMPE). St. Louis is the only metropolitan area to experience the loss of an NFL team within our window of 2012-2018 so this model is optimal in comparing St. Louis to a synthetic St. Louis whose team, which we shall call the St. Louis Synths, did not move. We interpret the difference between our synthetic St. Louis and the real St. Louis rates as the causal effect on crime of losing an NFL team. Table 1 displays the resulting weights. Because 143 areas were weighted in some way, we only include the top 30 locations ranked by the size of its weighting. The RMSPE (root mean squared prediction error) in this case is 180.3517 crimes per 100k inhabitants. Table 2 shows the predicted outcomes as compared to the true results.

As predictors and controls for the model, we use total crime (in the pre-period), area population, average income, age, race, the fraction of the city that is below the poverty line, unemployed, or male, as well educational factors, specifically the percentage that have graduated high school and have had any time spent in college. Inequality is one of the biggest socio-economic factors affecting crime as the higher income areas can create higher returns to crime, while the lower income areas can supply more people to commit crimes (Campaniello, 2011), which we capture using the percentage of the area population below the poverty level, average income, and unemployment. Age is also an important predictor, as most crimes are perpetuated by the young population (Imrohororghu et al., 2004); we specifically control for the rate of males between ages 15 and 25 the population most likely to be involved in crime.

Table 1: Unit Weights of Top 30 Locations

Area	Weight	Area	Weight
Dover, DE	0.287	Reading, PA	0.006
Sheboygan, WI	0.140	FortCollins, CO	0.006
Bridgeport-Stamford-Norwalk, CT	0.042	Rochester, NY	0.006
Odessa, TX	0.033	Bloomington, IN	0.006
Johnstown, PA	0.012	Bangor, ME	0.006
Napa, CA	0.010	York-Hanover, PA	0.006
AnnArbor, MI	0.009	Coeur d'Alene, ID	0.005
Indianapolis-Carmel-Anderson, IN	0.009	Ogden-Clearfield, UT	0.005
New Orleans-Metairie, LA	0.008	BoiseCity, ID	0.005
Chicago-Naperville-Elgin, IL-IN-WI	0.008	Gadsden, AL	0.005
LosAngeles-LongBeach-Anaheim, CA	0.007	Providence-Warwick, RI-MA	0.005
JeffersonCity, MO	0.007	GrandJunction, CO	0.005
Owensboro, KY	0.007	Bismarck, ND	0.005
Harrisonburg, VA	0.007	SanJose-Sunnyvale-SantaClara, CA	0.005
Beaumont-PortArthur,TX	0.007	Sebastian-VeroBeach, FL	0.005

Table 2: Predictions

Year	Y Treated	Y Synthetic
2012	4972.000	4982.284
2013	4570.000	4581.991
2014	4295.000	4303.787
2015	7936.000	7952.006
2016	6008.000	8145.418
2017	6071.000	8141.573
2018	4955.000	7556.094

Table 3: Predictor Balance

Variable	Treated	Synthetic
tot_crime(2012)	4972	4982.284
tot_crime(2013)	4570	4581.991
tot_crime(2014)	4295	4303.787
tot_crime(2015)	7936	7952.006
pop(2012(1)2015)	330	327.984
violent(2012(1)2015)	888.5	742.289
rob(2012(1)2015)	205.5	569.716
propcrime(2012(1)2015)	722.250	715.587
age(2012(1)2015)	41.321	40.872
asian(2012(1)2015)	0.021	0.029
amerin(2012(1)2015)	0.002	0.009
assault(2012(1)2015)	674	610.267
bgy(2012(1)2015)	926.5	843.985
black(2012(1)2015)	0.149	0.105
college(2012(1)2015)	0.381	0.466
gradhigh(2012(1)2015)	0.705	0.702
inctot(2012(1)2015)	1644630.143	1686710.936
kill(2012(1)2015)	197.5	112.158
male1525(2012(1)2015)	0.055	0.063
pover(2012(1)2015)	0.155	0.167
propcrime(2012(1)2015)	722.250	715.587
theft(2012(1)2015)	589.250	647.321
unem(2012(1)2015)	0.036	0.034
vtheft(2012(1)2015)	543.500	571.267
white(2012(1)2015)	0.803	0.808

Assumptions

For the difference between synthetic St. Louis crime rates and actual St. Louis crime rates to be interpreted as the causal effect on crime of St. Louis losing its NFL team, we follow the assumption that the synthetic St. Louis is an accurate representation of what would have happened had the Rams stayed.

One threat is if the convex hull assumption does not hold. By testing how well our selected combinations imitate the crime trends in the pre-period, we gain evidence for the synthetic St. Louis' accuracy. Figure 3 shows the difference in crime rates for synthetic St. Louis and actual St. Louis are very small in the pre-period. The reported RMSPE is $3.03X10^{-9}$, demonstrating that the crime rates in St. Louis can be very accurately imitated by a combination of the donors included.

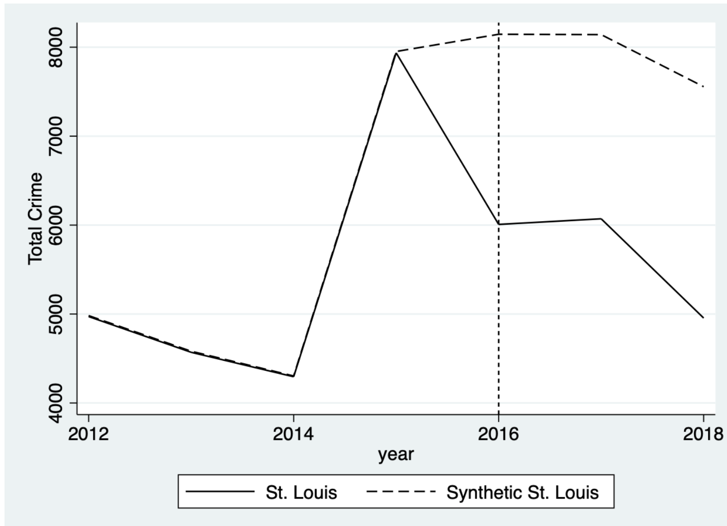

Figure 3: Fit and Divergence of Control

The crime data we use is reported voluntarily so there is a risk that biases in the reporting may bias our findings. If which precincts report is changing over time, the relationship between St. Louis and the donors may be changing. This would lead to the accuracy of the control being different in the pre-period and post-period and we would be unable to determine how much of our results are being driven by a decrease in the accuracy of our synthetic St. Louis. Table 4 shows that the participation rate is very high every year. With such high participation the potential bias from changes in who reports should be negligent. Additionally, because we restrict our donors to only include areas that were consistently reported, none of the areas in our sample are affected by shocks that may change participation rates for reporting crime.

Another potential bias arises from how crime is reported. Certain categories of crime are missing values in different years. If these missing values occur randomly and at the same rate in the pre-period and post-period, they should not impact the magnitude of the difference between our synthetic and actual St. Louis.

Another threat to identification is the possibility of exogenous shocks to our donor pool. Any policy that impacts actual crime rates could possibly change the relationship between the affected donors and St. Louis. If these donors are included in our synthetic control then the ability of the control to predict crime in the pre-period would be different from its ability to predict crime in the post-period, biasing our results. We did not find substantial changes in policing policy during the window 2012-2016

Table 4: Agency Participation Rate for the State of Missouri

Year	Total	Reporting	Percent
2012	640	637	99.53
2013	629	623	99.05
2014	636	631	99.21
2015	637	632	99.22
2016	621	617	99.36
2017	613	537	87.60
2018	603	520	86.24

Inference

The method of inference for synthetic control is rather straightforward. Because it acts as a causal application of predictive learning, and therefore has no interpretable parameter or estimating equation, we look at the difference in the predicted outcome of crime rates of synthetic St. Louis, or the St Louis Synths, and what actually occurred. Our robustness checks give us a greater understanding of the significance of this change. As seen in Table 6, 2016 is significant at the 5% level when compared to the placebos. This leads us to believe that the dramatic decrease in crime in 2016 is not a random event.

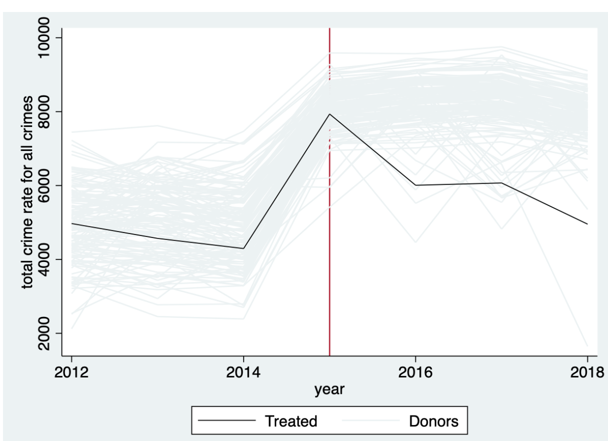

Figure 1: St. Louis Compared to Placebos

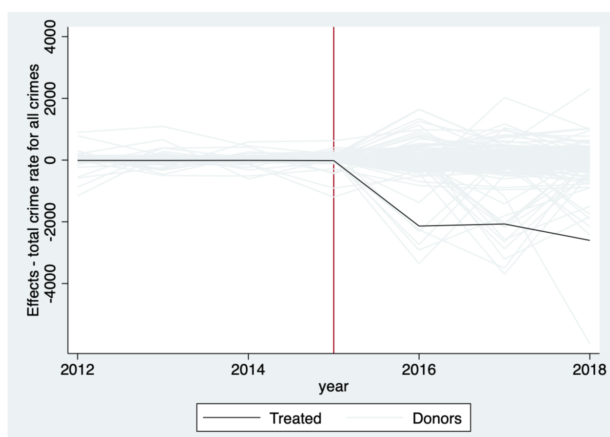

Figure 2: Effect of Treatment

Table 5: P-Values by Location

Rank	Area	P-Value	Rank	Area	P-Value
1	PUEBLO, CO	0.0069***	16	BALTIMORE-COLUMBIA-TOWSON, MD	0.1111
2	ROCHESTER, NY	0.0139**	17	SANJOSE-SUNNYVALE-SANTACLARA, CA	0.1181
3	RIVERSIDE-SANBERNARDINO-ONTARIO, CA	0.0208**	18	LACROSSE-ONALASKA, WI-MN	0.1250
4	YUBA CITY, CA	0.0278**	19	BLOOMINGTON, IN	0.1319
5	NAPA, CA	0.0347**	20	MCALLEN-EDINBURG-MISSION,T X	0.1389
6	LEBANON, PA	0.0417**	21	COEUR D'ALENE, ID	0.1458
7	DECATUR, IL	0.0486**	22	OKLAHOMA CITY, OK	0.1528
8	OWENSBORO, KY	0.0556*	23	LAFAYETTE, LA	0.1597
9	PUNTAGORDA ,FL	0.0625*	24	JACKSON, TN	0.1667
10	FORTWAYNE, IN	0.0694*	25	COLLEGESTATION-BRYAN, TX	0.1736
11	**ST.LOUIS, MO-IL**	**0.0764***	26	ROANOKE, VA	0.1806
12	SPRINGFIELD, MA	0.0833*	27	RACINE, WI	0.1875
13	COLUMBIA, MO	0.0903*	28	AMARILLO, TX	0.1944
14	DETROIT-WARREN-DEARBORN, MI	0.0972*	29	UTICA-ROME, NY	0.2014
15	PORT ST.LUCIE, FL	0.1042	30	LAKELAND-WINTERHAVEN, FL	0.2083

*** p<0.01, ** p<0.05, * p<0.1

Table 6: P-Values by Treatment Year

2016	2017	2018
0.034965**	0.055944*	0.006993***

*** p<0.01, ** p<0.05, * p<0.1

Figure 1 shows the crime trends over time for all areas included in our sample. Almost all these areas seem to follow the same basic trend over time, with a few negative spikes in the post-period that then converge to the average. Meanwhile, St. Louis's divergence from the main trend in the post-period does not immediately return to the average. Figure 2 shows more clearly that St. Louis's actual crime trends were significantly below predictions as compared to placebo tests for other areas. While each individual year is statistically significant, the comparable placebo years generally differ from the synthetic estimation for only a year before the gap closes. Meanwhile, St. Louis crime rates remain substantially lower over all three years. Using the ratio of RMSPE in the pre and post-periods we can determine that St. Louis's difference over the entire post-period is greater than 92% of the placebo areas. Using this ranking we can say that the probability of obtaining a result at least as significant as St. Louis's is 0.076.

In attempting to identify what drove this change, there are several possible culprits. One may be policing reform that inherently reduced the numbers of arrests or incidents with the police, though no such legislation for that year has been identified. Another may be that those who normally would commit crimes in association to the fray of a win or loss of their national American football team have substituted their fandom towards a different national sport. St Louis is home to two other national teams: the St Louis Cardinals in baseball, and the St Louis Blues in hockey. There are other potential substitutes for football fandom, but if fans did indeed substitute away from football then the substitutes seem to incite criminal behavior less frequently.

That being said, even if there is a move in a fan's favored team, that would not imply the fan stops being a fan of football, or even a fan of that specific team. Thus, we expect some of the decrease in crime to be driven by a lack of sporting events being hosted in St. Louis.

Section IV: Results

Figure 3 shows the main findings of this synthetic control. There is minimal prediction bias in the pre-period. that may not result in a surplus of variance in the bias-variance tradeoff given the size of the RMSPE. After this tight trend, there is a divergence in the year 2016 in which St Louis actually saw a significant decrease in crime, while the control shows that the crime rates for St Louis would be higher if the Rams were still in the city.

MRSPE: $3.03X10^{-9}$

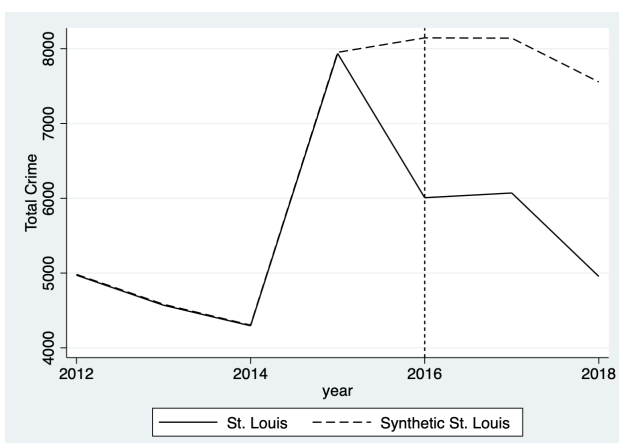

Figure 3: Fit and Divergence of Control

Robustness

We run a difference in difference as well using the same data and set up as the synthetic control model. We estimate the effect of the Rams moving on crime with the equation, and find a large and statistically significant effect on crime.

$$\text{Crime} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \text{St. Louis*Post} + \varphi\text{year} + \psi\text{area} + \boldsymbol{\beta}\text{X} + \epsilon.$$

Table 7: Differences in Differences

VARIABLES	(1) Without Controls	(2) Controls	VARIABLES	(1) Without Controls	(2) Controls
treat	-2,127***	-2,137***	male1525		1,891
	(59.86)	(87.53)			(3579)
pop		-0.95	unem		5235
		(1.200)			(4912)
male		3252	pover		2058
		(2945)			(2036)
age		0.76	inctot		0.00
		(52.750)			(0.00)
white		-1,378	college		-1258
		(6800)			(2203)
black		-2339	gradhigh		-679.0
		(7126)			(3003)
asian		4242	Constant	5,098***	6141
		(8256)		(60.070)	(7537)
otherrace		-354.70	Observations	1008	1008
		6812	**R-squared**	**0.893**	**0.895**

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Mechanisms and Heterogeneity

We do not believe that all crime is equally affected by the presence of an NFL team. Other literature has found evidence of sporting events leading to increases in property crime and violent crime (domestic violence). We expect that the decrease in crime is primarily driven by decreases in these areas.

We theoriorize two primary mechanisms for which the presence of an NFL team impacts crime rates: game day activities and emotional investment.

NFL games lead to surges in both traffic and population present in the hosting city. Travel to and from the stadium creates increased opportunity for crime to property crime given the normal population of the city. Effectively the population is artificially inflated so crime rates per 100,000 people are just capturing a surge in the number of people interacting.

The other mechanism is emotional investment. Sports fans invest in the outcome of sporting events and so these outcomes impact their emotional state. These emotional shocks can cause increased propensity to commit some crimes.

Section V: Conclusion

Overall, crime rates in St. Louis have decreased after the Rams relocated to Los Angeles, driven by decreases in property and violent crime. Previous studies have shown more specific instances of sports events impacting crime and we show in this study that these individual effects have an important impact on aggregate crime.

Better data collection could help our results, allowing us to match on more years in the pre-period as well as include more donors. While there is little room for improvement in predicting crime rates in St. Louis with our current methodology, it is possible that matching the real crime trends in the pre-period would be harder with more years and would be aided by more donors. More donors would also allow for more placebo tests that could verify the significance of our results with greater precision.

Further research has many questions left to consider. The impact on St. Louis should be compared to other cities impacted by the relocation of an NFL team. The cost of the crime effects should be compared to the economic benefits of having a sports team in the city. Changes in crime rates could be compared by month to determine if they occur only during the NFL season, or if there are more enduring effects on attitudes that affect crime even outside of the season.

When an NFL team moves away, games stop being played but it is possible that fans remain invested in the outcomes of the team that moved away. Concentration of fans following a team that left should be explored alongside the changes in crime.

Long term trends should also be explored to find if the impact of NFL teams moving dissipates over time or if the presence of an NFL team has a consistent yearly effect.

Additionally, it would be worthwhile to explore potential positive impacts of sports on crime that may be partially offsetting the negative impact we found. Potential mechanisms are that sports may increase youth participation in sports programs that may decrease the probability of future crime. It is also possible that sports spectatorship could be a substitute for crime for some people. More carefully considering how demographics of perpetrators is influenced by the increase in crime caused by NFL teams could possibly reveal some of these trends.

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