The Impacts of Philadelphia Traffic Enforcement Reform on Traffic Stops, Racial Profiling, and Public Safety

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Background

Traffic stops are one of the most common ways police interact with the public, (Tapp & Davis 2024). Unfortunately, this method of enforcement exhibits racial bias, can escalate violently, and doesn't necessarily improve traffic safety, (Tapp & Davis 2024, Pierson et. al 2020, Sarode et al 2021, Ward et al 2024). This has led to efforts to reform traffic stop policy, including in Philadelphia. In March 2022, Philadelphia's Driving Equality Law went into effect, reclassifying some minor vehicle code violations as secondary violations, meaning they cannot be enforced using a traffic stop unless a primary violation is also observed.[1] The bill specifies the city council's intent to, among other things, "prevent racial disparities… and protect public safety," (City of Philadelphia 2022).

The Driving Equality Law targets the use of pretextual stops by police, the practice of stopping a vehicle for a typically minor offense with the intention of conducting an unrelated criminal investigation. Pretextual stops were established as legal by Whren v. United States in 1996, but the contribution of pretextual stops to racial profiling has led some jurisdictions to reconsider the use of pretextual stops. Previous literature on the effects of attempting to limit pretextual stops mostly show reductions in traffic stops of minorities, with the specific findings varying. Similar policies to Philadelphia's have been studied in several other major cities. In Los Angeles, the intervention was found to reduce traffic stops for minor violations and stops of minorities without the overall number of traffic stops decreasing or crime increasing, (Matsuzawa 2024). In St. Paul, the policy was found to nearly eliminate traffic stops for vehicle violations and reduce stops for minorities more than whites. A short-term increase in criminal

[1] The reclassified violations are: an expired registration of less than 60 days, a temporary registration displayed in the wrong location, an insecurely fastened registration plate, a single light not lit, an obstruction of the side or rear windows, a bumper violation, a missing certificate of inspection, and a missing emissions inspection.

activity was found in St. Paul which was reversed in the long term, (Naddeo & Pulvino 2023). In Seattle, no increase in driving under the influence or drug crimes was found, (with that being the only result reported), (Peter et. al 2023).

Limited literature also exists evaluating the impacts of changes to the legal status of pretextual stops. A 2012 Washington court case removed a restriction on pretextual stops. This decision and the subsequent changes to police training were found in one study to increase the amount of minority drivers stopped compared to white drivers, (Rushin & Edwards 2021). However, another study attempting to separate the effects of the case and Washington's legalization of marijuana the same year found no effects on racial disparities in traffic stops derived from the legal decision, (Asirvatham & Frakes 2022). The limited literature leaves the impact of major court decisions regarding pretextual stops inconclusive.

Other strategies to reduce racial profiling have also been studied. A Connecticut program that identifies and works with police departments with racial disparities in traffic stops was found to reduce stops of minorities in identified towns, driven primarily by a decrease in pretextual stops, with a moderate decline in clearance rates of property crimes but no other negative impacts to public safety, (Parker et. al 2024). Federal investigation into the Seattle Police Department was found to reduce stops in minority neighborhoods without harm done to public safety, (Campbell 2025). However, a similar investigation in Cincinnati (along with public scrutiny following a police shooting) resulted not only in decreased overall arrests especially in black communities, but a sharp rise in felony crimes, (Shi 2005). A consent decree between New Jersey and the Department of Justice regarding racial disparities in highway stops led to no gains in equity despite institutional reforms, (Fagan & Geller 2020). This broader literature regarding a diversity of strategies to decrease racial profiling reveals that results differ greatly not only by type of intervention but by instance and location.

The spatial dynamics of traffic stops and racial profiling is an area with very limited literature. Traffic stops in Houston and police-civilian contacts in Oakland have been found to be spatially correlated with areas with a high concentration of black and hispanic residents, (Roh & Robinson 2009, Schnell & Boehme 2024). Adjacently, parking ticket fines have been found to be unequally distributed in Los Angeles, with more tickets issued in black neighborhoods, (Brazil 2018).

This paper evaluates the Driving Equality Law's success in achieving its stated goals by examining changes in traffic stops, characteristics of traffic stops, and parallel trends related to public safety. This is done through difference in differences estimation and exploratory geographic analysis. This shows a reduction in escalation of traffic stops of black and latino drivers through frisks and searches due to the policy without a significant change in number of stops. In parallel but not necessarily related, there was no significant change in crashes or crash fatalities, significant increases in general crime, and a decrease in driving under the influence arrests. This bears some similarities and some differences to findings regarding similar policies in different cities, evaluating the specific Philadelphia law while continuing to show the heterogeneity by location found in existing literature. The paper also shows heterogeneity in the geographic drivers of different outcome variables, showing that outcomes differ even within

Philadelphia and suggesting that more research needs to be done to identify the likely complex mechanisms behind city-level policy effects.

Data and Mechanism

The main dataset used in this paper is the “Vehicle & Pedestrian Investigations” dataset obtained from OpenDataPhilly, Philadelphia’s official open data repository. It contains all Philadelphia Police Department investigations of vehicles, drivers, and pedestrians from 2014 to present, with information including where and when the interaction occurred, demographic information, and stop outcomes. This paper uses a subset of this dataset limited to vehicle investigations from January 2021 through December 2024, with the lower limit selected to maximize pre-intervention period while excluding the irregular traffic stop patterns during 2020 due to the impacts of the COVID-19 pandemic and the upper limit selected due to data availability at the time analysis was performed. The dataset has good completeness for most variables but lacks completeness for reason for stop, with the vast majority of stops in the pre-intervention period lacking a specified reason for stop. This prevents direct evaluation of whether the reasons for stops changed following the intervention, eliminating what is a main finding in many similar papers.

Other datasets used in this paper are the “Part 1 & Part 2 Crime Incidents (2006-Present)” dataset from the City of Philadelphia and the “Crashes data” dataset from OpenDataPhilly, both used to establish parallel trends in public safety. The “Hispanic or Latino Origin by Race” dataset compiled by the National Historical Geographic Information System using US Census data is used to reference the racial and ethnic demographics of different areas of the city.

This paper estimates difference-in-differences models for the effects of the intervention on traffic stop numbers and characteristics. This quasi-experimental approach calculates how a variable changes in the post-intervention period for both a treated group and a non-treated group, subtracting those differences to estimate the impact of the intervention on the treated group. This helps isolate the effects of a single intervention and allows the use of a control group with initially differing attributes. This paper works off of the premise that the minor offenses listed in the new Philadelphia law are (in the pre-intervention period) mostly used to stop black and latino drivers as part of pretextual stops. Therefore, black and latino drivers can be used as a treatment group and non-black or latino drivers can be used as a control. These models can be described:

$$y=\beta 0+\beta 1*treatment+\beta 2*post+\beta 3*treatment*post+e$$

where *treatment* is an indicator for whether a driver is in the control group (not black or latino=0) or in the treatment group (black or latino=1), and *post* is an indicator for points in time before (0) or after (1) the intervention began on March 1, 2022. The effect of the treatment is therefore captured by the coefficient $\beta 3$.

Difference in differences, in addition to the assumptions for the ordinary least squares model, requires an assumption of parallel trends, meaning that the trend of the treatment group must be parallel to the assumed counterfactual trend of the treatment group. If this assumption is false, the estimate will end up measuring other trends besides that caused by the intervention. This is checked most simply by constructing parallel trends plots, found in the Appendix.

Examining the plots for each variable difference in differences is used to model, the trends are not perfectly parallel but appear close enough to continue.

Unfortunately, availability of data does not allow the same quasi-experimental models to be estimated for parallel trends in public safety. Ordinary least squares is used to provide the public safety context in the pre- and post-intervention periods in comparison to national trends when possible. This paper also uses exploratory geographic data analysis to better understand whether trends differ geographically and what areas of Philadelphia are experiencing and driving changes.

Traffic Stop Findings

Table 1 displays the results of two sets of estimators. The first, labeled ordinary least squares, is a simple model showing whether the variables significantly changed from the pre-intervention period to the post-intervention period with no controls. It is labeled according to the formula:

$$y=\beta 0+\beta 1*post$$

Where *post* is an indicator for points in time before (0) or after (1) the intervention began, so $\beta 1$measures the magnitude of the difference in the variable from the pre- to the post-intervention period. SE signifies the standard error of that coefficient, p signifies p-value at a 95% significance level, and 95% CI signifies the corresponding confidence interval.

The second set, labeled difference in differences, is the main method described earlier, which isolates the effect of the intervention using the treatment group of black and latino drivers and the control group of other drivers. *β3,* as described earlier, is the coefficient measuring the effect of the intervention. The other columns correspond to the coefficient the same as the ones in the ordinary least squares set.

Table 1: Results of Ordinary Least Squares and Difference in Differences Models for Traffic Stop Attributes

Variable	Ordinary Least Squares				Difference in Differences			
	β1	SE	p	95% CI	β3	SE	p	95% CI
Stops per Month	-380.17	500.56	0.451	[-1367.76, 627.37]	-703.9	416.77	0.095	[-1531.64, 123.84]
Frisk Rate	-0.022	0.001	0	[-0.023, -0.020]	-0.0159	0.002	0	[-0.020, -0.012]
Search Rate	-0.0235	0.001	0	[-0.025, -0.022]	-0.0126	0.002	0	[-0.016, -0.009]
Contraband Found Rate	-0.0114	0	0	[-0.012, -0.011]	-0.0045	0.001	0	[-0.007, -0.002]
Arrest Rate	-0.0083	0.001	0	[-0.009, -0.007]	-0.0002	0.001	0.907	[-0.003, 0.003]

First considering the ordinary least squares, all rates of stop characteristics had significant reductions, while the reduction in stops per month was not significant. This alone doesn't imply any causal relationship with the intervention, rather just describing that the changes were or were not significant. Next, considering the difference in differences, there is no significant reduction in stops per month or arrest rate, but there is a significant reduction in frisk rate, search rate, and rate of contraband being found. This means that black and latino drivers, the demographic the intervention should affect the most, experienced a reduction in these rates of significantly greater magnitude than other drivers. This suggests that the 2022 law caused changes in these variables. It also strongly suggests that the intervention is not what caused the significant decrease in arrest rate. Figures 1-3 show this difference visually, comparing the change in variables between black and latino drivers and other drivers for the three variables with significant changes.

Figure 1A: Rate of Frisk for Black and Latino Drivers

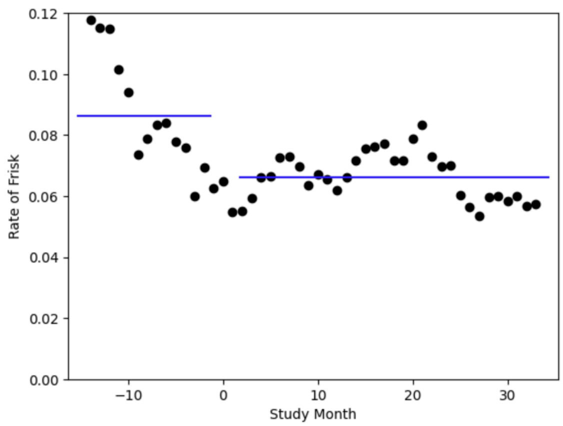


Figure 1B: Rate of Frisk for Non-Black or Latino Drivers

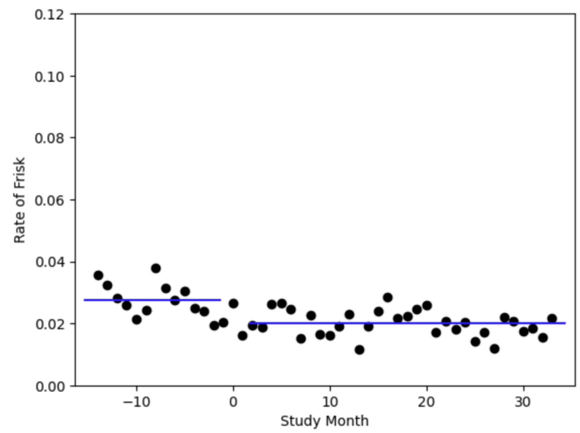


Figure 2A: Rate of Search for Black and Latino Drivers

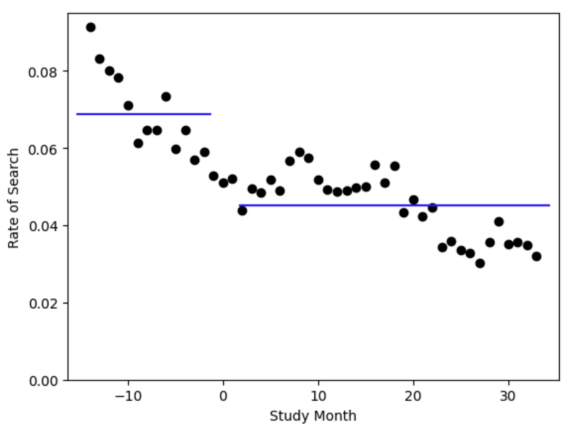


Figure 2B: Rate of Search for Non-Black or Latino Drivers

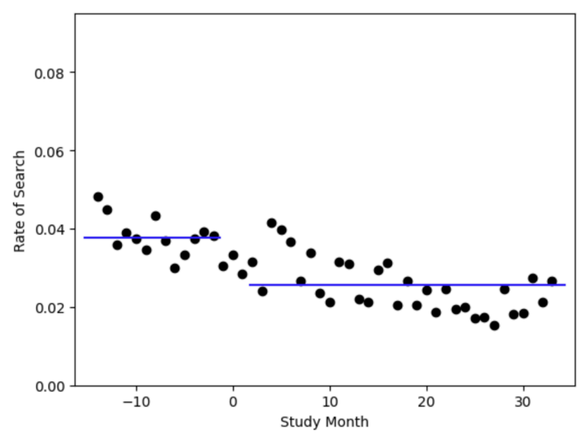


Figure 3A: Rate of Contraband Found for Black and Latino Drivers

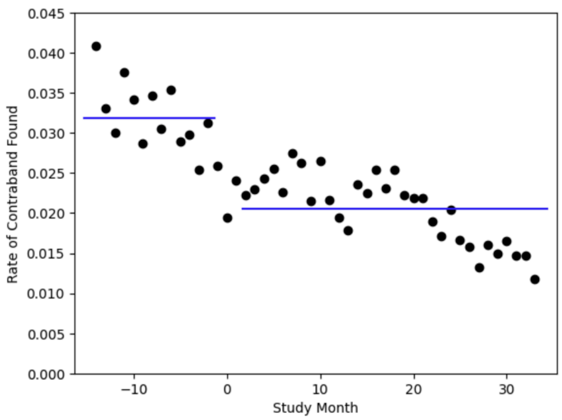
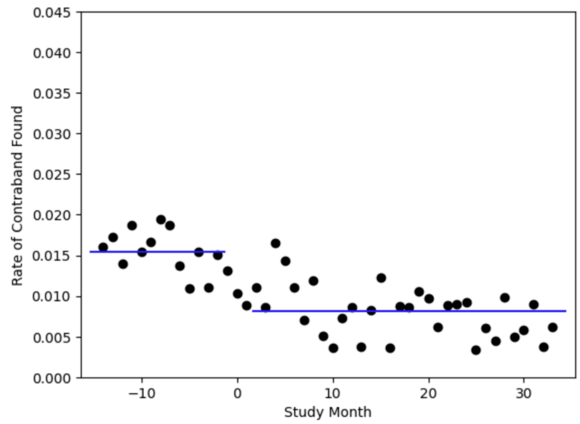


Figure 3B: Rate of Contraband Found for Non-Black or Latino Drivers



Parallel Trends Findings

This paper explores parallel trends of two relevant elements of public safety: vehicle crashes and crimes. Table 2 displays the results of ordinary least squares models showing that the number of crashes per month significantly decreased from the pre-intervention period to the post-intervention period, while there was no significant change in crash fatalities per month (notably the fatality sample size is much smaller). Note that this dataset is limited to December 2023 at the latest, a year earlier than the time frame of the other datasets used. No causal inferences should be drawn by this due to the lack of control group, but it at least shows that there is no drastic increase in crashes that could be cause for concern in the limited post-intervention period shown.

Table 2: Results of Ordinary Least Squares Models for Traffic Safety

Variable	Ordinary Least Squares			
	β1	SE	p	95% CI
Crashes per Month	-103.682	30.844	0.002	[-166.364, -41.000]
Crash Fatalities per Month	0.195	1.213	0.873	[-2.269, 2.659]

Table 3 shows the results of ordinary least square models for frequency of crime. In Philadelphia, crimes are separated into Part 1 and Part 2 crimes. Part I crimes are violent offenses including aggravated assault, rape, and homicide. Part II crimes include simple assault, prostitution, and many non-violent offenses. Homicide is included here due to special interest as an especially violent crime, theft is included as it is a main driver of changes in Part 1 Crimes, and driving under the influence (DUI) is included due to increased relevance to traffic enforcement.

Table 3: Results of Ordinary Least Squares Models for Crime

Variable	Ordinary Least Squares			
	β1	SE	p	95% CI
All Crimes	2424.483	341.347	0	[1737.387, 3111.579]
Part 1 Crimes	1866.088	245.403	0	[1372.117, 2360.059]
Part 2 Crimes	558.395	145.842	0	[264.829, 851.961]
Homicide (included in pt 1)	-13.5294	3.226	0	[-20.022, -7.036]
Theft (included in pt 1)	1149.702	131.316	0	[885.376, 1414.028]
DUI (included in pt 2)	-44.5756	8.015	0	[-60.709, -28.442]

The table shows that all variables changed significantly, with overall crimes and larger categories increasing while homicide and DUI occurrences decreased. Taking the same pre- and post-intervention periods, national violent crime did not change significantly, as seen in Table 4, suggesting that these changes are Philadelphia-specific. However, there is again no evidence for causal inference here due to the lack of a control group or other convincing quasi-experimental method.

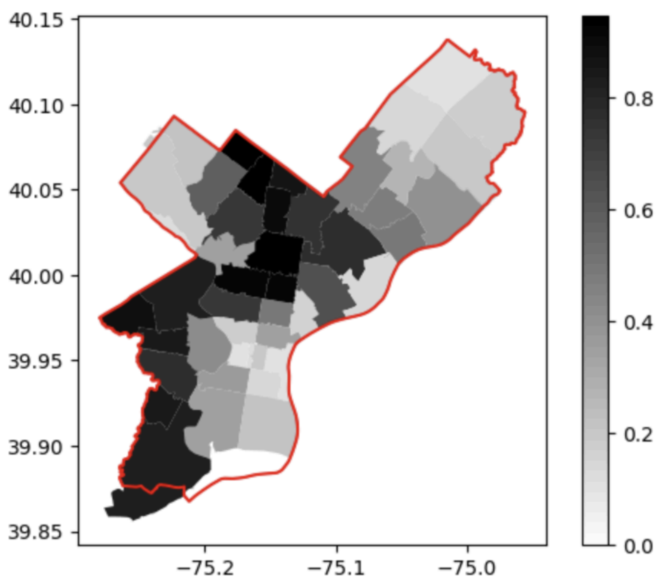
Table 4: Results of Ordinary Least Squares Models for National Violent Crime

Variable	Ordinary Least Squares			
	β1	SE	p	95% CI
National Violent Crime	-387.555	1120.312	0.731	[-2642.626, 1867.517]

Geographic Findings

Figure 4 shows a map of Philadelphia and surrounding zip code tabulation areas (ZCTAs) with approximate percent black or latino and city limits in red. ZCTAs provide a manageable but sufficiently detailed size unit to perform exploratory analyses and have demographic information available.

Figure 4: Approximate Percent Black and Latino by Zip Code with City Limits



These ZCTAs are used as regions for difference in differences estimators for the same traffic stop variables as the whole-city analysis, allowing insight into what significant changes different parts of the city are and aren't experiencing. For example, even though differences in differences didn't find any significant impacts on number of stops for the entire city, some ZCTAs did have significant changes in number of stops, as seen in Figure 5. Figures 5 through 9 show the ZCTAs which have significant difference in differences results, with the magnitude and sign of the change indicated by color.

Figure 5: Difference in Differences Coefficients in Zip Codes with Significant Difference in Differences Results for Number of Stops

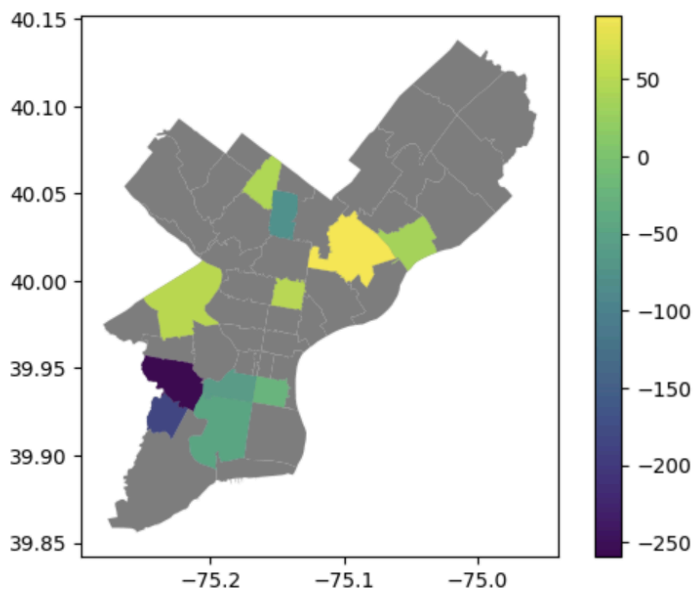


Figure 6: Difference in Differences Coefficients in Zip Codes with Significant Difference in Differences Results for Individual Frisked

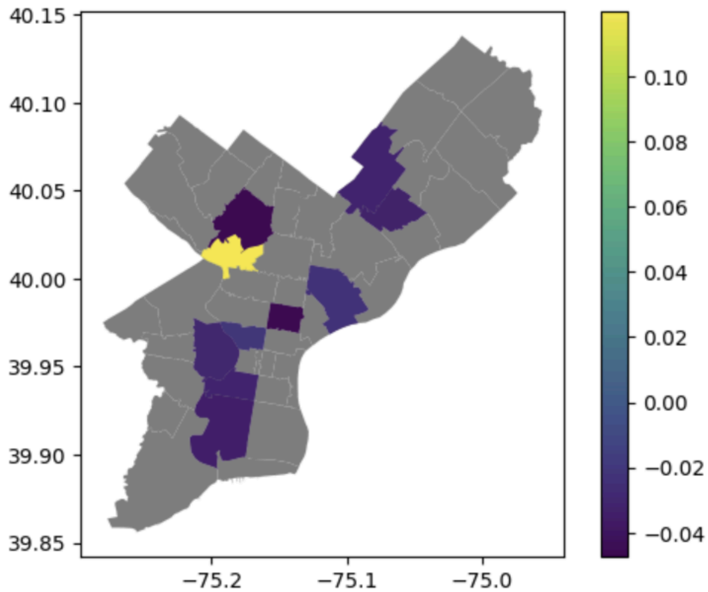


Figure 7: Difference in Differences Coefficients in Zip Codes with Significant Difference in Differences Results for Contraband found

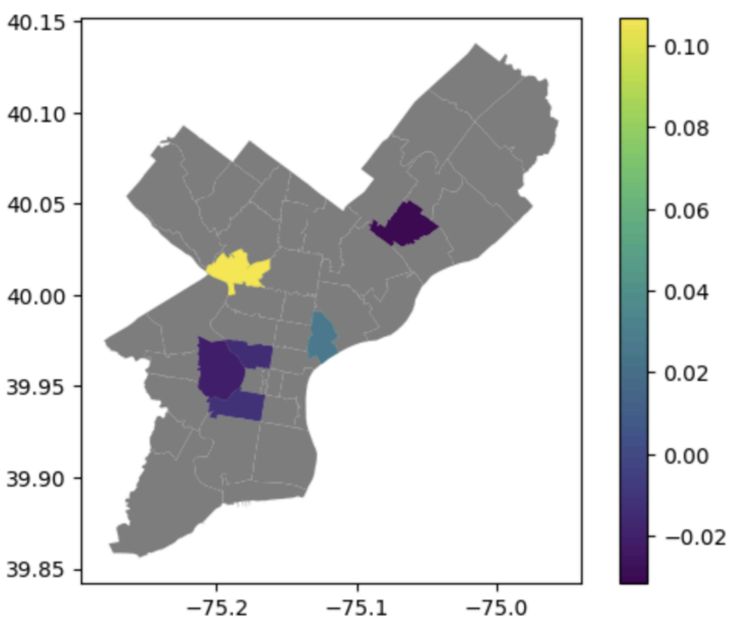


Figure 8: Difference in Differences Coefficients in Zip Codes with Significant Difference in Differences Results for Individual and/or Vehicle Searched

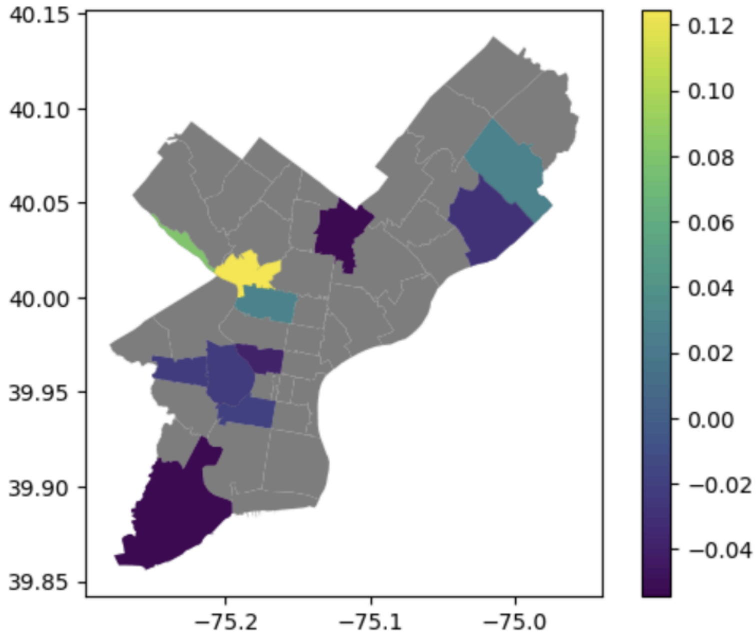
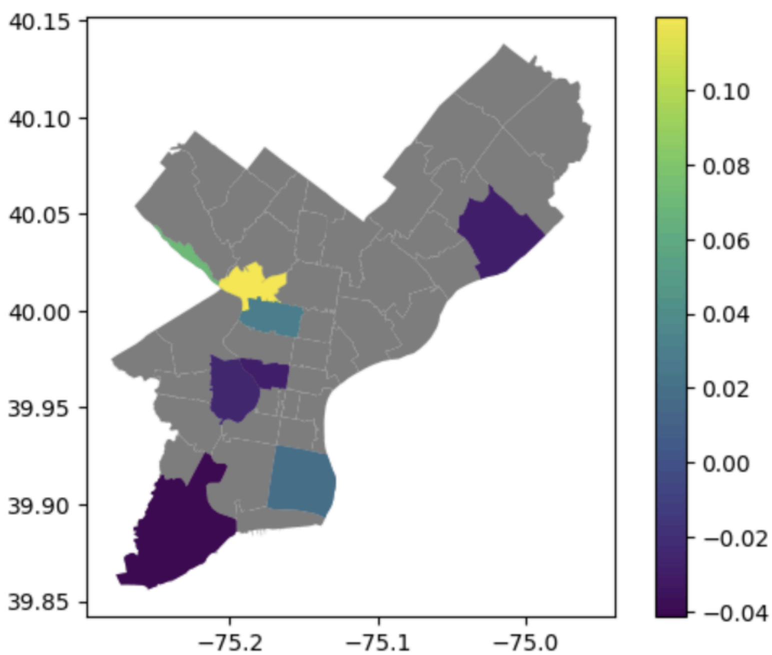


Figure 9: Difference in Differences Coefficients in Zip Codes with Significant Difference in Differences Results for Arrest



It's apparent that the significant effects in many ZCTA differ from the city as a whole. Relationships between the variables are also suggested by these figures. A significant change in number of stops doesn't seem to be related to a significant change in any of the stop attribute variables, but the attribute variables seem geographically related to each other. In particular, ZTCA's that have a significantly heightened or lessened rate of search after the intervention seem to typically show a similar trend in rate of arrest, despite the fact that rate of arrest was not significant at the whole-city level. Also, interestingly, significant changes are not as cleanly or obviously linked to racial makeup of a ZCTA as one might think.

Discussion

The Philadelphia Driving Equality Law seems to have had some positive effects for traffic stop equity with a few potential downsides. Black and Latino drivers did not see less traffic stops, but saw greater reductions in rates of being frisked and searched or having their vehicles searched compared to other drivers, suggesting that the law worked to reduce the unequal treatment of minorities in traffic stops. However, arrest rate did not change significantly compared to non-Black and Latino drivers, suggesting that bias in the form of arrests may still be present. Additionally, the rate of contraband being found decreased along with frisk and search rates for black and latino drivers compared to others, showing a decrease in police efficacy.

It was difficult to sufficiently address parallel trends, but there are some notable findings. First, regardless of causality there was no significant increase in crashes or fatalities following the policy, easing potential concerns of worsened traffic safety. The general increase of crime is likely impacted by many other factors besides this policy, but the decrease of DUI cases is more concerning. DUIs decreasing isn't a good sign unlike some other crimes decreasing, because they are only recorded if caught, unlike theft, for example, which is typically reported by the victim. While there's no ability to draw a causal inference, it's worth considering that this policy may have impeded the polices' ability to enforce DUI law. The decrease in homicide, on the other hand, could help ease concern that any limiting of contraband enforcement would lead to a spike in gun violence.

Geographic analysis also reveals a few interesting trends. First, it seems that relative changes in rates of frisks, searches, contraband being found, and arrests are geographically linked, but are not obviously geographically linked to relative changes in number of stops. Additionally, any geographic relation to the demographics of an area is far less close than expected. This, along with the general heterogeneity shown, suggests that the police response to the policy may be geographically heterogenous. A simple example of this would be if some police officers responded to the policy by stopping less black and latino drivers, while others stopped similar demographics for different offenses. This could lead to some ZCTA's having positive significant difference in differences coefficients for number of stops, others having negative ones, and others yet having no significant results, much like is seen in Figure 5. Data on reason for stop could help determine the mechanisms of change and degree of heterogeneity, but unfortunately is impossible with this dataset.

Conclusion

This paper adds to the literature observing varying effects across different locations and iterations of policy intended to reduce racial profiling. Unfortunately, future research is needed to solidify some of the conclusions in this paper, theorize on mechanisms, and make policy recommendations, in large part due to the absence of reason for stop data. While some results are uncertain and potential issues exist in contraband and DUI enforcement, there are also clear positive effects. Black and Latino drivers have seen a reduction in frisks and searches compared to other drivers, and there is no evidence of worsened driving safety from the lack of enforcement of part of the traffic code. This paper should also encourage geographic analysis of policies like this in addition to city wide trend observation due to the potential for geographic heterogeneity.

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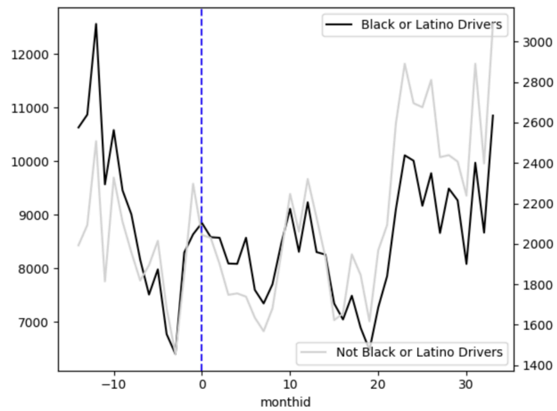
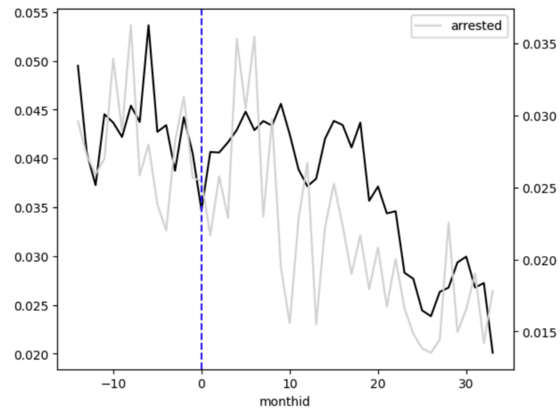
Appendix: Parallel Trends Plots

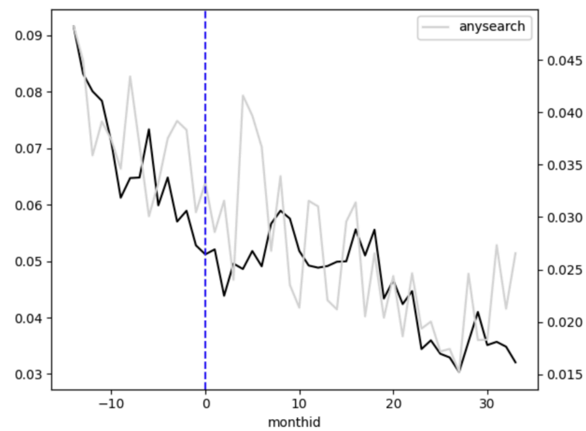
Number of Stops Per Month



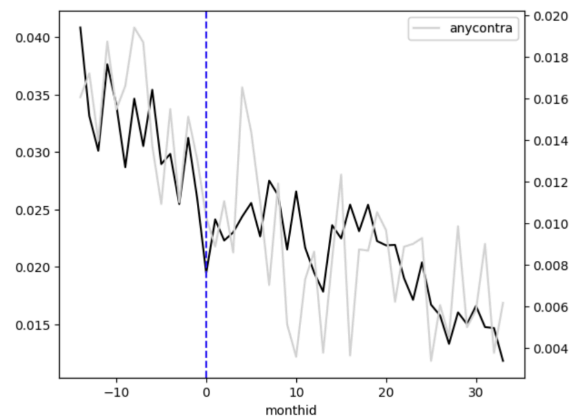
Rate of Stops Resulting in Arrest



Rate of Stops Resulting in Search



Rate of Stops Resulting in Contraband Found



Rate of Stops Resulting in Individual Frisked