An Investigation into New York’s Contemporary Stop-and-Frisk Policy

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Abstract

This paper is an investigation into New York’s implementation of stop-and-frisk. Salient critiques of the policy are racially-motivated searches and low effectiveness in finding contraband, all reasons to critics use to call for the halt of the practice. Proponents of the policy point to the value of “order maintenance” and deny any racial or ethnic inequalities in its implementation. We will address some current critiques by looking into how New York’s stop and frisk policy has changed over time due to a changing social and political climate as well as whether or not stops change based on specific events. We will do so through an analysis of the stops in New York from 2003 to 2015, analyzing race and gender distribution, as well as the fruitfulness of frisks across this time period.

Keywords: stop-and-frisk, New York City, broken windows policing, general trends, racial inequality

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Introduction

Stop-and-frisk is a very controversial policy in this day and age; it is the result of policies and practices that involve stopping, questioning, and sometimes searching for weapons and contraband. The implementation of stop-and-frisk within New York has changed a lot over time. Although the practice was initially implemented to address crime suspicion and protect officers, this is far different from the practice's current contemporary form. In this paper, we provide an analysis of the total stops from 2003 to 2015 within New York looking into general trends over time and the impact of specific events. In our results, we see that the claims of inequality with regards to race within stops are supported by our figures, and there is a lack of effectiveness when large volumes of stops and frisks are implemented. We also found that events have very little impact on policy implementation with regards to stop-and-frisk and large changes are more likely attributable to changes within culture and judiciary decisions.

The paper will contain the following sections. First, we will outline the history of stop-and-frisk, as well as the current state of the policy and debates surrounding it. We will then discuss where we obtained our data, the methods of analyses we chose to use, and their effectiveness. Next, we will look at the analyses we conducted and draw conclusions from their results in order to answer our research questions and address various talking points that have been used to debate stop-and-frisk policy.

A Brief History of Stop-and-Frisk in New York

In 1968, *Terry v. Ohio* established what came to be known as a *Terry* stop, meant to be a stop of anyone suspected of having committed a crime, in the process of committing a crime, or about to commit a crime (Torres, 2015, pp. 931). The Terry decision also stated that frisks would be allowed as a means of protecting officer safety (2015, pp. 932).

It seems that New York City police departments have moved away from the spirit of the *Terry v. Ohio* decision's purpose and towards the use of stop-and-frisk to show a strong police presence and maintain order within society. Multiple factors have led up to this perspective on crime prevention: increased support of crime control measures in the judicial system, the war on drugs, and the adoption of "broken windows" policing (2015, pp. 932). James Wilson and George Kelling are the originators of the "broken windows" theory introduced in 1982, with the policy popularized in the late 1990s. "Broken windows" is the idea that visible signs of crime encourages further crime, and that targeting and eradicating lower level crimes will promote an environment order that in turn prevents larger, more serious crimes. They wrote the book (not quite a book, but article) on the matter, entitled "The Police and Neighborhood Safety: Broken Windows". In this article, published by Atlantic Monthly, they cite the shift towards resource efficiency and crime solving as the reason the link between order-maintenance and crime prevention has been ignored (1982).

Kelling and Wilson's work inspired policy implementations of "broken windows" policing that political figures like Mayors Guiliani and Bloomberg and Police Commissioner Bill Bratton staunchly support. However, Kelling and Wilson acknowledge that the Police Foundation, found no link between increased foot patrols and reduced crime in a study done just years prior (1982). Instead of focusing on factual evidence and statistics, the burden of proof of the theory is placed on anecdotes from a Newark police officer that describes classifying “regulars” and “strangers” his community to target criminals, an unashamed endorsement of profiling. Kelling and Wilson concede that “some of the things he did probably would not withstand a legal challenge” (1982). The emphasis on unsubstantiated and subjective parameters, such as police intuition, to promote order has been called to attention in recent years as ineffective and dangerous. Nonetheless, Wilson and Kelling’s work was accepted at the time as having “ample evidence of the strength of their model”, and was even believed to bring more public support and increased efficiency to police departments (Corbett & Harris, 1997, pp. 68).

Also pertinent is the historical judicial tendency towards crime prevention that informed the development of modern stop-and-frisk . Jose Torres speaks more about this in his article “Race/Ethnicity and Stop-and-Frisk: Past, Present, Future”. The most salient effect of this trend is that “maintaining order” through 1960s court decisions meant perpetuating systems of de facto segregation (2015). In essence, historical court cases informed by segregation and unsubstantiated police theories espoused by politicians contributed to today’s ineffective stop-and-frisk policy.

Contemporary Stop-and-Frisk

Within the past decade, the constitutional basis of stop-and-frisk has increasingly been called into question. At its most basic level, the stop-and-frisk policy is constantly challenging the bounds set forth by the 4th Amendment, protecting against unreasonable searches and seizures without probable cause. The conversation regarding stop-and-frisk's legality was amplified after court cases were brought against the NYPD and the city itself, including *Daniels v. City of New York* in 2003. The case claimed racial bias in stop-and-frisk patterns, ultimately mandating that policies employed by the NYPD be remediated and monitored (Torres, 2015, pp. 933). Cases like this shifted the legal focus from 4th Amendment violations to the increasingly clear infringement of citizenship rights and equal protection of the law laid out in the 14th Amendment.

In response to constitutionality challenges, political figures in support of the stop-and-frisk policy, chiefly Mayor Bloomberg, attempted to counter the claims. Bloomberg believed stop-and-frisk was a necessary component in his espoused "tough on crime" stance to reduce the amount of contraband (guns and drugs). However, as Jay Newberry Highlights in his book, *Racial Profiling and the NYPD : The Who, What, When, and Why of Stop and Frisk*, the large jump in frisks was not accompanied by a proportionate decrease in crime rate (2017, pp. 13). In fact, from 2010 to 2011 the number of frisks increased by nearly six fold and yet the decrease in crime was miniscule and could not be attributed to stop-and-frisk (2017, pp. 13).

Anecdotally, citizens also noticed disproportionate targeting of non-white neighborhoods. One example is Brownsville, Brooklyn, where 52,000 stops were made over the course of just 4 years in a one block radius (Baker, Rivera, & Roberts, 2010). This is the equivalent of one stop per resident each year. Police entered data describing individuals who were stopped into a database for tracking, regardless of whether or not the person stopped was suspected of committing a crime or not. Police even stopped and entered children into the database for riding their bikes on the sidewalk, arguing these records have the potential to solve future crimes (2010). Articles highlighting cases like this fueled controversy surrounding the policy.

Legal tension surrounding stop-and-frisk culminated in a final trial challenging the constitutionality of New York's implementation of their stop-and-frisk policy: *Floyd v. City of New York*. On August 12, 2013, Federal Judge Shira A. Scheindlin ruled that stop-and-frisk was being implemented unconstitutionally, stating that the NYPD had a "policy of indirect racial profiling" (Goldstein, 2013). Bloomberg publicly disagreed with the ruling, directing the city to appeal the decision before implementing the required reforms, though policies were eventually implemented. The increase in arrests that accompanied the decreased rate of frisks began to contradict the NYPD's assertion of the effectiveness of stop-and-frisk (Newberry, 2017, pp. 14). Despite the city's change in their implementation of stop-and-frisk, controversy regarding the policy is still relevant in New York, as well as other large cities across the country.

Overview of Our Data

To further understand New York City's implementation of stop-and-frisk, we obtained data from the New York City Government's website, found under their NYPD reports and analysis page. The website published data from 2003 to 2016 in CSV format and data from 2017 and 2018 in excel files. The database contained variables for race, gender, physical description, exact coordinates of stops, what contraband was found, X and Y coordinates of stops, and many more variables. In determining our research questions, we narrowed our interests to the general trends of stop-and-frisk were over time with regards to a changing political and social climate and whether or not individual events impacted the racial makeup of stop-and-frisks.

For general trends, we focused mostly on creating visualizations that illuminated the overall effects of the policy on the city. We analyzed race and gender variables to understand who was more likely to be stopped and frisked, as well as whether or not any sort of contraband was found during these frisks. The dataset provided incredibly specific data on the type of contraband found, from knives or drugs all the way up to machine guns. In our analysis, we chose to focus just on whether or not anything incriminating at all was found on an individual, not the severity of the contraband. We only used the data from 2003 to 2015, as the format of variables for 2016 through 2018 was much different and there were higher quantities of missing data. Our final dataset was a culmination of these years of data with different daily totals for different variables we generated in order to perform our analysis.

Results and Analysis

Methodology

To analyze our data, we used the statistical software Stata. The first step in the analysis was formatting the data to then be consolidated into a single data set. The most extensive part of reformatting was adjusting our date variable, changing the type to be compatible with Stata's handling of time data. To do this, we made the dates strings, making sure they were all eight characters long – months prior to October were only seven characters long initially, missing the succeeding '0' in the encoding for their month values. We then converted the date strings back to numbers and ran Stata's process for generating dates in a readable format for graphs and regressions. We left this underlying date variable within our dataset, but also generated an additional variable with the same information in a human-readable format so that we could accurately interpret our results.

After formatting each year's data, we appended files together to create one main data file with about 9 million observations. We then generated variables for each individual stop that we wanted to consider in our analysis. These variables operated in Boolean logic – holding a value of 1 if a characteristic was true and a value of 0 if it was false. In the end we had a stop variable for each race and gender (blackmalestop, blackfemalestop, whitemalestop, etc.) and a frisk variable for each race and gender, as well as a variable for whether or not contraband was found. We also created generic stop and frisk variables just indicating whether an individual was stopped (which always held a value of 1) or frisked regardless of characteristics. From here, we collapsed the database by our date variable, summing our Boolean variables to get daily totals for the number of people stopped, frisked, with contraband, and stopped or frisked within each race and gender.

Using our daily totals, we could then generate variables for the percentage of total stopped and total frisked each race accounted for and the percentage of frisks that resulted in contraband found, what we will call our fruitful search variable. This final database allowed us to look at how data changed throughout our time period (2003 to 2015).

To address our first inquiry about general trends of stop-and-frisk over time, we looked at monthly totals for each year, as well as yearly totals stratified by race and gender. This allowed us to look at the changes in volume over time without focusing on seasonal or weekly variations due to holidays, the day-of-week effect, and other things of that nature. We then looked at fruitful search rates graphed against time as well as total number of frisks. Finally, we looked at the percent of stops and frisks each race made up daily and monthly; Due to the volatility of day-to-day sums within our dataset and the length of the time period we are studying, it is clearer in monthly comparisons, as opposed to daily ones, what overall trends are. These comparisons allowed us to gain insights into the change of volume of stops and frisks as well as the makeup of stops by race and gender.

When looking into whether or not certain events could impact the implementation of stop-and-frisk, we chose three different events. All of the events were dates of black men being killed by white police officers, as we were most interested in the racial makeup of stops and felt these events would show most clearly whether or not the racial composition of stops and frisks changed. We chose 3 cases to focus on -- Sean Bell, who was killed on November 25, 2006, Eric Garner, killed July 17, 2014, and Freddie Gray, killed April 19, 2015. We chose Bell and Garner's death to gain insight into differences in changes pre- and post-Black Lives Matter in New York, and Freddie Gray to see if national events that occurred outside of New York could change the implementation of policy as well. To execute our regressions, we set up three different variables for each event: variables set to one for a week after the event, set to one for two months after the event, and set to one for a year after the event. We then ran regressions for these taking into account both day-of-week and month-of-year variables we created, to minimize the effects of the volatility of the data on our regressions.

When first running the regressions, we used measured changes in total numbers for Black and White citizens who were stopped. These variations were large, and we were initially unsure how to interpret this data. Further examining the results, it would be inaccurate to make assumptions off of total number stopped for each group and instead we opted to measure the change in percentage of the total stopped each race accounted for. This allowed us to look at the change in volume of stops, as well as the impact on who is being stopped.

The data obtained also included XY coordinates of each stop, a valuable metric that we used to create a series of maps of one month before and after the shootings of Sean Bell, Eric Garner, and Freddie Gray. In order to do this, we used Stata to create 6 different CSV files containing stops one before and after each police shooting. Each CSV was imported into QGIS, an open source program for creating GIS visualizations. We decided that we wanted to visually show the changes in where police were stopping people in the immediate aftermath of these events, best exemplified by a heat map of each stop. To do this, each CSV file was uploaded to QGIS and converted the format of the Projection Coordinate Reference system, provided in State Plane Coordinates - New York Long Island to the standard WGS 84 in order to alter the projections to a format more widely used. Next, using the GIS packages, we extended the radius of each stop to 1500 feet to allow the points to overlap, creating a heatmap effect. Each map is colored in “Continuous Mode”, separating the overlapped radiuses into 52 separate color classes. Since the scale is separated into 52 classes, it became difficult to publish a color ramp on this map.

General Trends Over Time

To look at general trends over time, the first thing we did was graph yearly totals of stops, using the strata of race and gender to get a better sense of the makeup of who is stopped. This data is found in Figures 1, 2, and 3.

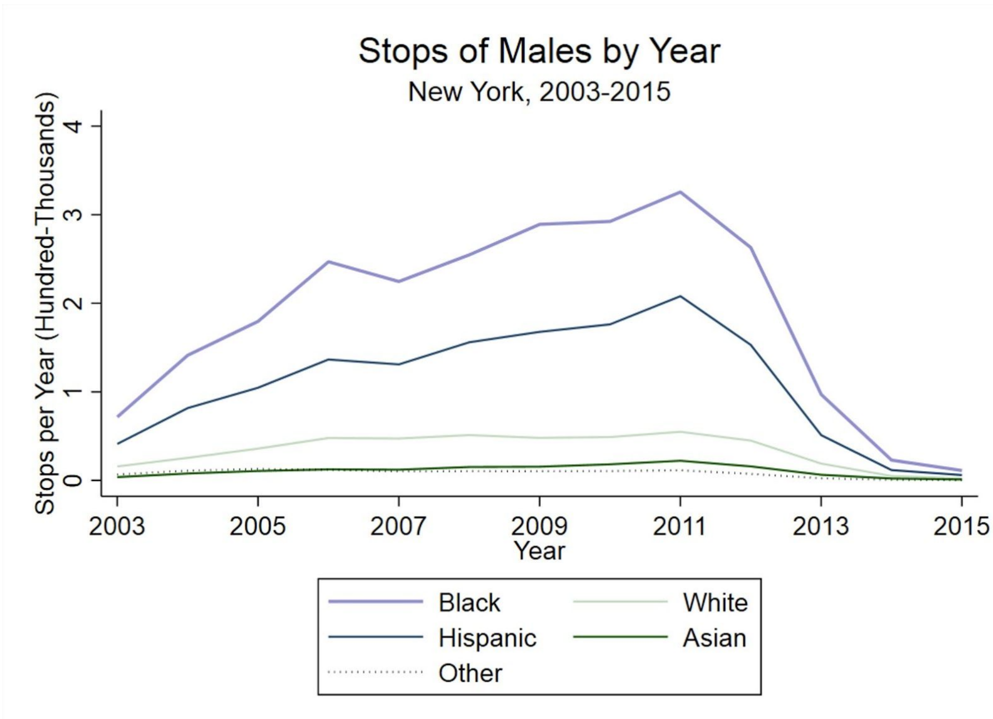


Figure 1. Total Yearly Stops of Males. This figure illustrates the differences in total Males stopped based on race.

This graph is separated by race and compounded by total frisks per year. Race encoding is as follows: other includes entries coded as American Indian/Alaskan, Unknown, and Other. Hispanic entries are encoded in the original database as black-hispanic and white-hispanic. Variables for Black, White, and Asian were all originally specified not altered for the sake of this analysis.

This graph shows a consistently higher number of black male citizens being searched as opposed to any other race that is categorized. The higher amount of searches of black males also means the higher rate of searches, considering that Black males make up 13% of New York City’s population. In keeping with the expected trend of racially motivated searches, Hispanics and Whites have the next highest amounts of searches. Particularly interesting is the crossing Asian and Other lines, consistent with the expectation that Asians are perceived as the lowest threat level.

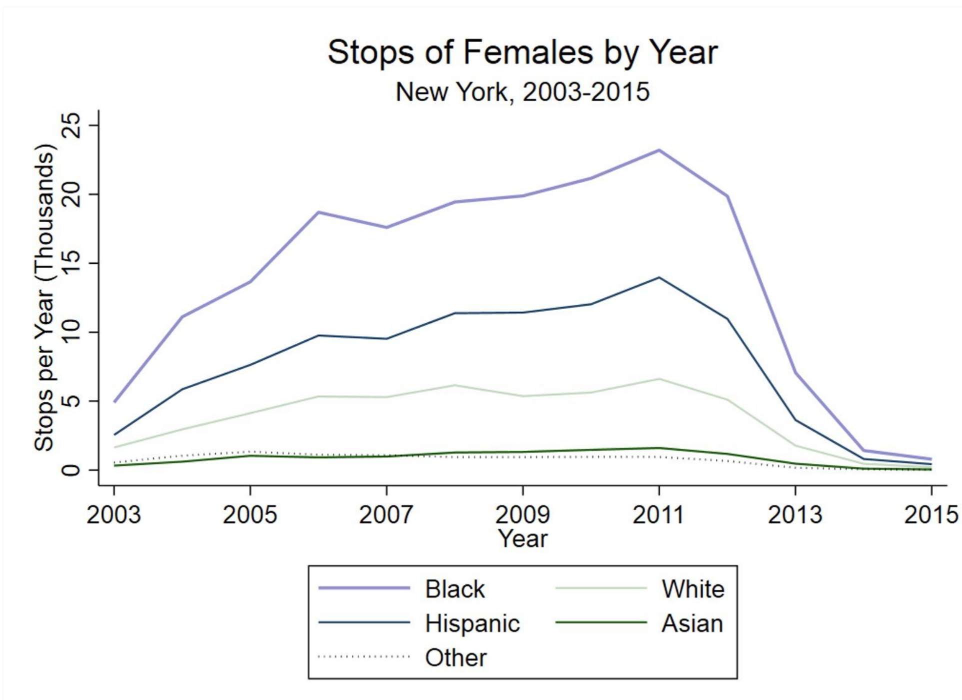


Figure 2. Total Yearly Stops of Females. This figure illustrates the differences in total females stopped based on race.

Similar to the graph of males, this graph also shows a consistently higher amount of black females being searched as opposed to any other race. In keeping with the expected trend of racially motivated searches, Hispanics and Whites again have the next highest amounts of searches. Particularly interesting is that the crossing Asian and Other lines, occur in relatively the same place as the male graph. Important to note here is that the general trends in this graph closely mirror the male graph, at a drastically different scale (hundreds of thousands versus thousands).

Figure 3. Total Yearly Stops by Gender. This figure illustrates the differences in total individuals stopped based on gender.

This figure shows the drastic difference in the volumes of men versus women that are searched. As noted above, the differences in the scales (hundreds of thousands versus thousands) of searches by gender show the significantly higher stops of males, who are perhaps more likely to be considered suspicious. It is also important to illuminate that though they make up equal shares of the population, men are at least 100 times more likely to be searched than a woman, not accounting for differences in race.

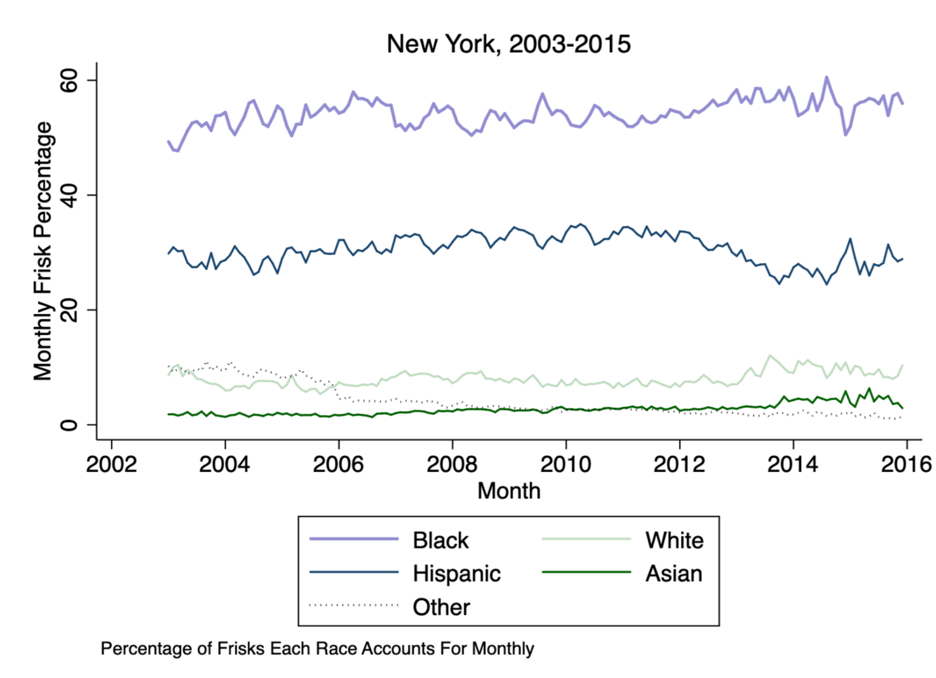


Figure 4. Percent of Monthly Frisks for Each Race. This figure illustrates the percentage of overall frisks that each race accounts for monthly.

This is a graph compounded by every month in the dataset, and shows the percent of stops that became frisks for each race. The general trend shows Black citizens are frisked at a higher rate than their Hispanic, White, and Asian counterparts. This difference gives weight to the conjecture that racial profiling is at play in both stops and stops that turn to frisks.

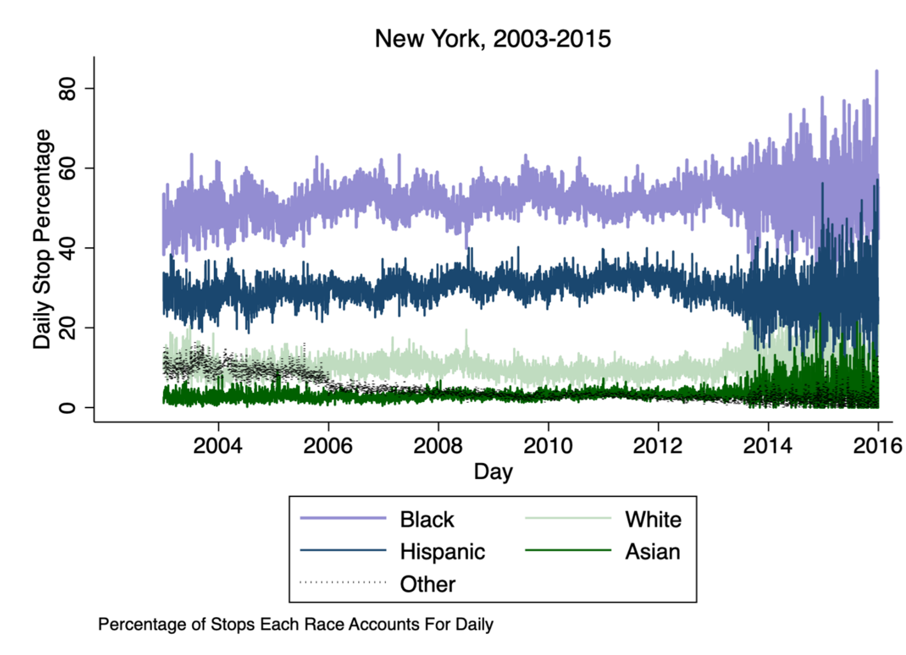


Figure 5. Percent of Daily Stops for Each Race. This figure illustrates the percentage of overall stops that each race accounts for daily.

This graph measures the same data as Figure 4, but with stops summed daily. This also shows the consistently higher rate of black frisks, but the width of each line increases into 2014. This graph is illuminating as it shows the volatility of daily searches increasing: with increased variability there is more overlap in percentage even when general monthly trend appears to be the same, perhaps an indication of change towards less prejudice.

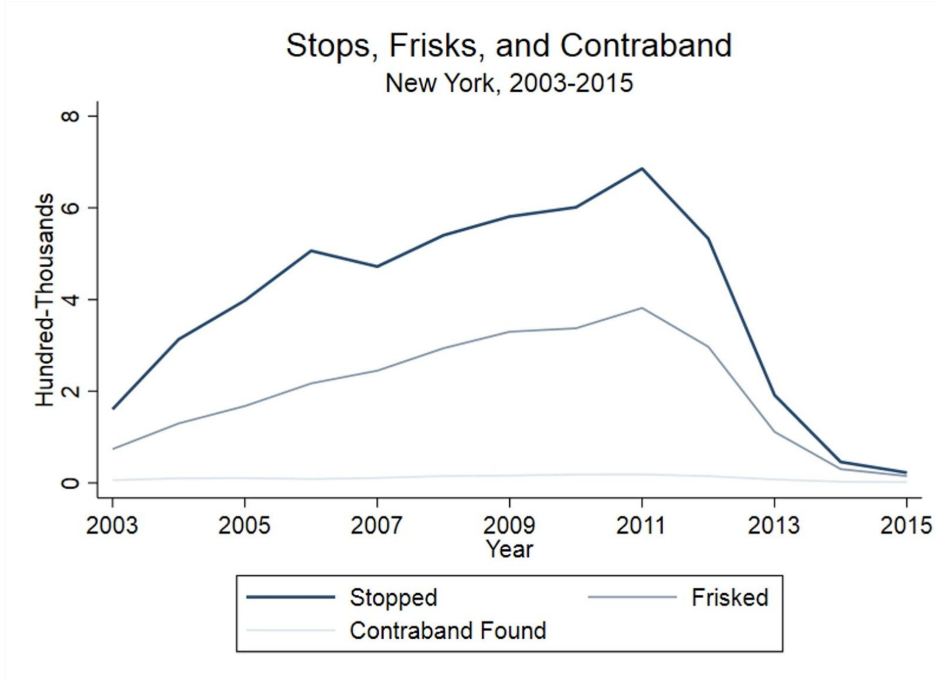


Figure 6. Total Stops, Frisks and Fruitful Searches. This figure illustrates the total number of stops and frisks compared to the total number of individuals found with contraband on their person.

This graph depicts the total stops, frisks, and fruitful searches summed yearly. Clearly the number of frisks per year closely follows the total stops each year, following similar upward and downward trends. However, the amount of contraband, on this relative scale, is a fairly flat line that doesn't visually vary, regardless of amounts of stops. This allows us to conjecture, at least descriptively, that the amounts of stops doesn't increase the rate of getting guns and drugs off the street.

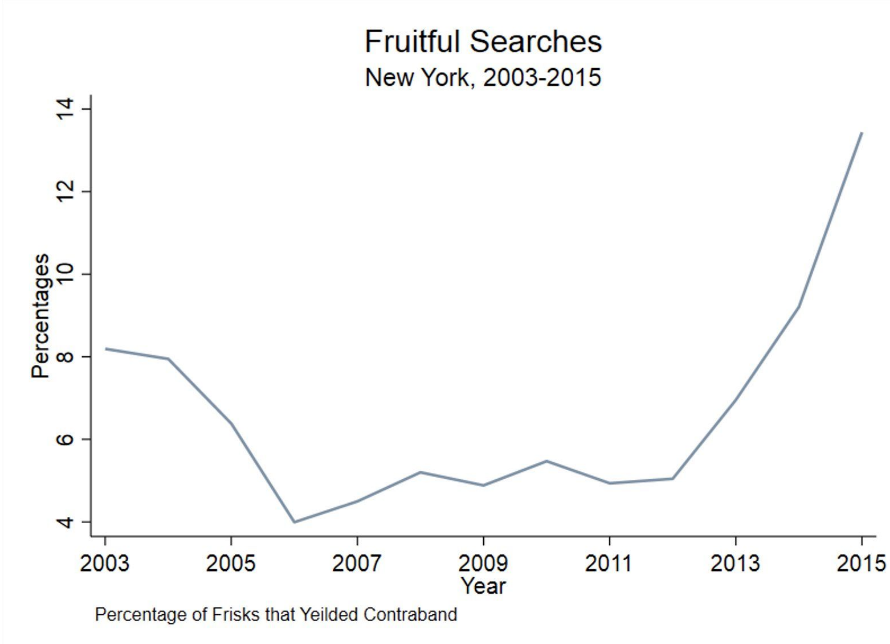


Figure 7. Fruitful Search Rate. This figure illustrates the percentage of individuals frisked yearly who are found with contraband on their person.

This figure further examines the relationship between stops, frisks, and contraband found. In ways, this graph follows an opposite direction to the trends of total stops, experiencing a downward turn in fruitful searches each time total stops are increased between year to year. This is most visually represented after 2011, when the number of total stops begins decreasing and the rate of fruitful searches shoots up. Though, it is also important to note that the most effective frisks have ever been is 14%, not quite a rousing endorsement of the policy.

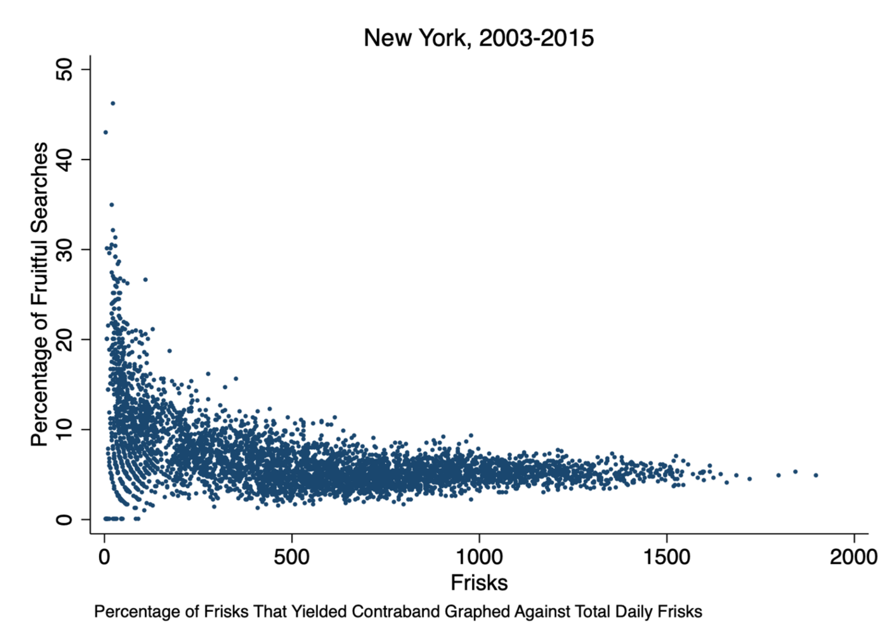
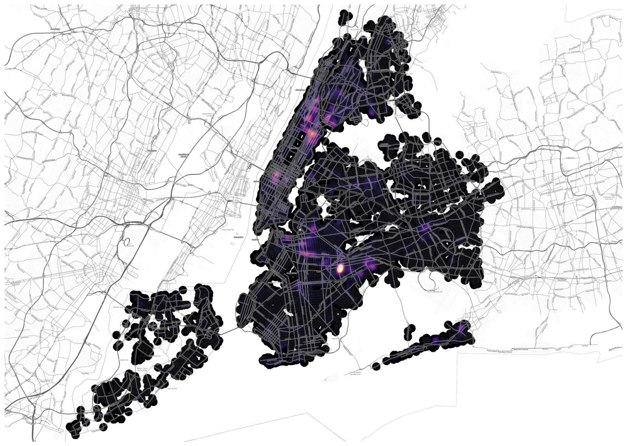


Figure 8. Daily Fruitful Search Rate vs Total Frisks.

This figure illustrates the relationship between the number of frisks in a day and the percentage of those frisks that yield contraband. This graph is particularly interesting, as it exemplifies the result that fewer frisks per day are able to yield a much higher percent of contraband found. This result also demonstrates heteroscedasticity, the concept that variability of a variable is unequal across the range of values of a second variable that predicts it. For example, for a day with a low number of frisks, the rate of fruitful searches could range from 0% to 47%. Whereas if as the number of frisks increase to say 1500, the rate of fruitful searches only ranges from 4% to 8%. This means that a higher number of frisks per day almost always has a low fruitful search rate while lower number of frisks per day could have both high and low fruitful search rates, providing support to the idea that increased quantity of searches does not increase the likelihood of finding contraband.



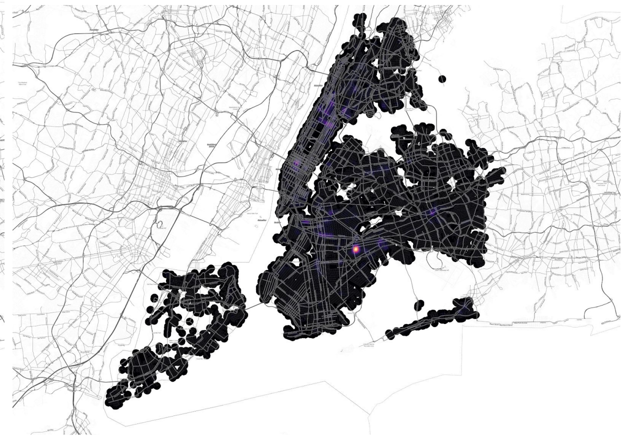


Figure 9. Stops 1 month before Sean Bell's death .

Figure 10. Stops 1 month after Sean Bell's death.

These heatmaps created in QGIS show an interesting pattern in the geography of stops in New York. Figure 9 shows a wide spread of searches within the city, with one mild hotspot in midtown Manhattan, some hotspots in the Bronx, and one major hotspot in Brownsville, Brooklyn. Brownsville is a neighborhood in Brooklyn with a 76.7% black population. Sean Bell was killed in Jamaica, Queens, a highly diverse neighborhood. There is a slight hotspot in Queens in Figure 9. Figure 10 shows the brilliance of the hotspots diminishing and virtually disappearing, creating a more uniform spread of searches across the city. The hotspot in Brownsville remains, but is less drastically targeted as Figure 9, perhaps due to media articles published regarding the disproportionate amount of searches in Brownsville.

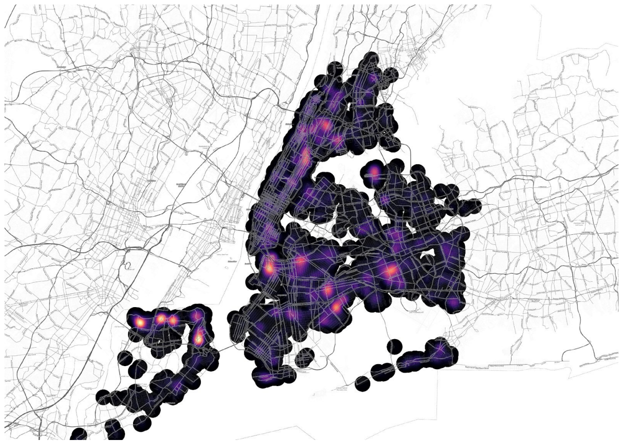


Figure 11. Stops 1 month before Eric Garner's death.

Figure 12. Stops 1 month after Eric Garner's death.

Figure 11 shows more targeted searches across certain boroughs, namely Brooklyn and Staten Island. There are most notably 4-5 hotspots in close proximity on upper Staten Island, where Eric Garner was killed. Figure 12 shows a clear decrease in the number of hotspots, especially in Staten Island, which visually shows a shift in police presence allocation. In addition, the bright hotspot in Brooklyn is a public housing project in Bedford-Stuyvesant called Sumner Houses. Bedford-Stuyvesant is currently 49% black, much higher than the New York City average of 26%, providing support for the racially applied implementation. However, its rate of violent crimes per capita is greater than that of the city as a whole and some police presence in the neighborhood has shown to be effective, perhaps explaining the higher rate of stops (Bautista 2017).

Figure 13. Stops 1 month before Freddie Gray's death.

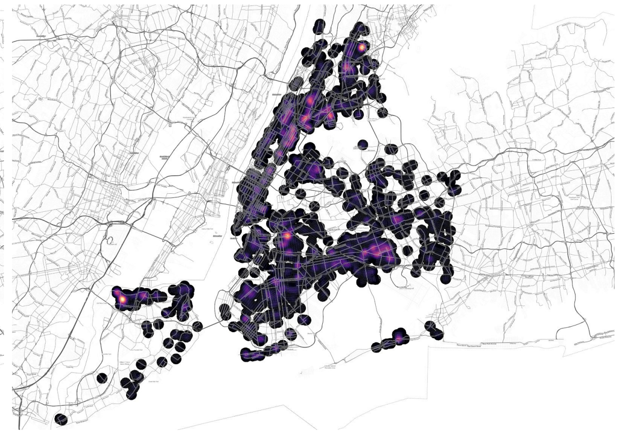


Figure 14. Stops 1 month after Freddie Gray's death.

Figure 13 shows hotspots mainly in the Bronx, western Staten Island, and some in Queens. Figure 14 shows less bright but similar hotspots as Figure 13, showing little change in geographic police presence priorities the months before and after Freddie Gray's death. This goes to show that national events, such as Gray's Baltimore killing, do not impact the geographic distribution of stops and does not actively inform NYPD policing priorities.

Impact of Individual Events on Stop and Frisks

In looking at individual events, we picked the deaths of three black men at the hands of white police officers to analyze. We hypothesized that these events would cause racial tension in communities, and thus would make an impact on the racial makeup of stops and frisks easiest to detect. We chose Sean Bell and Eric Garner's death to see if the Black Lives Matter movement would impact the way police responded to protests in terms of stop and frisk. Sean Bell was killed in 2006, prior to the Black Lives Matter movement and Eric Garner's death occurred one year after Black Lives Matter's founding, 2014. To measure the impact of events outside of New York on the policy, we chose to analyze Freddie Gray, who was killed in 2015 in Baltimore, as well.

In order to measure the effects of these events, we created three different variables for each death: one that had a value of one for a week after the event (named using first initial + last initial of the victim + "15"), one for two weeks (first initial + last initial + "30"), and one for a year (first initial + last initial + "year"). We then ran regressions for each of our dependent variables using these generated intervention variables, accounting for day of the week and month of the year to control for the volatility in our data. At first, we ran the regressions against the total number of people stopped, black people stopped, white people stopped, and fruitful searches to see if this changed the values. We realized that in terms of totals, the change in the entirety of people stopped was the only meaningful regression, seeing as the gap in the number of black vs white people stopped was already so large it was hard to make sense of the varying changes in number of people stopped. To address this challenge, we ran the regressions against the percentage of total stops made up of black and white people and the percentage of frisks that were fruitful. This allowed us to observe change in volume using our regression of total stops, and change in the effectiveness and actual makeup of stops using our percentage regressions.

We checked the regressions for a range of outcomes that could indicate various things. One hypothesis is that events and their subsequent protests could cause racial tension that resulted in angered police acting on impulse. If this were the case, we would expect to see a decrease in the percentage of frisks that were fruitful–indicating frisks based less on suspicion and more on personal sentiments–an increase in the percentage of total stops that black people account for, and possibly a decrease in the percentage that white people account for. These changes would indicate that police respond by lashing out against communities that challenge their authority. A different hypothesis is that the events led to efforts to minimize political repercussions, meaning we would expect to see a decrease in fruitful searches again, but a decrease in the percentage of total stops that black people account for. This decrease would indicate efforts to avoid further political scrutiny with regards to police policy. If we saw inconsistent changes across the three events that were substantive–meaning some events lead to changes in either direction and others did not–that would indicate that social and political contexts are important in determining whether or not an event will impact New York's policing in one of the two ways above and how it will do so. Furthermore, if both Sean Bell and Eric Garner's deaths led to substantively significant changes in percentages and volume, but Freddie Gray's did not, we can assume that only events within New York will impact the stop-and-frisk policy. Lastly, if the events do not impact policy at all, then we would expect changes to be inconsequential.

```
. regress percentWhite SB15 SB30 SByear i.day i.month

      Source |       SS       df       MS              Number of obs =    4748
-------------+------------------------------           F( 20,  4727) =   24.73
       Model |  3282.21489    20  164.110745           Prob > F      =  0.0000
    Residual |  31374.5684  4727  6.63731086           R-squared     =  0.0947
-------------+------------------------------           Adj R-squared =  0.0909
       Total |  34656.7833  4747  7.30077593           Root MSE      =  2.5763

------------------------------------------------------------------------------
percentWhite |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        SB15 |    -1.3488   1.339883    -1.01   0.314    -3.975596    1.277995
        SB30 |   .0224622   .9300266     0.02   0.981    -1.800823    1.845748
      SByear |    .967624   .1429614     6.77   0.000      .687353    1.247895
             |
         day |
          1  |   .8208538   .1399341     5.87   0.000     .5465177     1.09519
          2  |   1.983488   .1399348    14.17   0.000     1.709151    2.257826
          3  |   1.985696   .1398849    14.20   0.000     1.711457    2.259936
          4  |   1.906465   .1398849    13.63   0.000     1.632225    2.180704
          5  |   1.224927   .1399345     8.75   0.000       .95059    1.499264
          6  |   .6508885   .1399332     4.65   0.000     .3765542    .9252227
             |
       month |
          2  |   .5703913   .1858912     3.07   0.002     .2059581    .9348246
          3  |   1.206832   .1814948     6.65   0.000     .8510179    1.562647
          4  |   .9418527   .1829998     5.15   0.000     .5830878    1.300618
          5  |   .9530049   .1814931     5.25   0.000     .5971938    1.308816
          6  |   .9493367   .1830008     5.19   0.000     .5905698    1.308104
          7  |   .9793652   .1814931     5.40   0.000     .6235542    1.335176
          8  |    .703996   .1814948     3.88   0.000     .3481816     1.05981
          9  |   .7030978   .1830001     3.84   0.000     .3443323    1.061863
         10  |   .4843506   .1814931     2.67   0.008     .1285396    .8401617
         11  |   .2614027   .1834353     1.43   0.154     -.098216    .6210214
         12  |   .5203153   .1825094     2.85   0.004     .1625118    .8781187
             |
       _cons |   8.289485   .1581469    52.42   0.000     7.979443    8.599527
------------------------------------------------------------------------------
```

```
. regress percentBlack SB15 SB30 SByear i.day i.month

      Source |       SS       df       MS              Number of obs =    4748
-------------+------------------------------           F( 20,  4727) =   16.40
       Model |  6999.34987    20  349.967493           Prob > F      =  0.0000
    Residual |  100888.181  4727  21.3429618           R-squared     =  0.0649
-------------+------------------------------           Adj R-squared =  0.0609
       Total |   107887.53  4747  22.7275185           Root MSE      =  4.6198

------------------------------------------------------------------------------
percentBlack |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        SB15 |  -1.380936   2.402693    -0.57   0.565    -6.091333    3.329462
        SB30 |   2.993311   1.667733     1.79   0.073    -.2762236    6.262846
      SByear |  -.1633253   .2563599    -0.64   0.524    -.6659102    .3392596
             |
         day |
          1  |  -.4612547   .2509313    -1.84   0.066    -.9531971    .0306876
          2  |  -1.795123   .2509325    -7.15   0.000    -2.287067   -1.303178
          3  |  -1.852238   .2508431    -7.38   0.000    -2.344008   -1.360469
          4  |  -1.807245    .250843    -7.20   0.000    -2.299015   -1.315476
          5  |  -1.322602    .250932    -5.27   0.000    -1.814545   -.8306582
          6  |   -.165396   .2509297    -0.66   0.510     -.657335    .3265431
             |
       month |
          2  |  -1.277771    .333342    -3.83   0.000    -1.931277   -.6242659
          3  |  -1.864873   .3254583    -5.73   0.000    -2.502923   -1.226823
          4  |  -.9960456   .3281572    -3.04   0.002    -1.639387   -.3527047
          5  |  -.4710353   .3254553    -1.45   0.148    -1.109079    .1670088
          6  |  -.2659058    .328159    -0.81   0.418    -.9092504    .3774387
          7  |   .7085547   .3254553     2.18   0.030     .0705106    1.346599
          8  |    1.10678   .3254583     3.40   0.001     .4687305     1.74483
          9  |   .8413002   .3281578     2.56   0.010     .1979581    1.484642
         10  |   .6203422   .3254553     1.91   0.057    -.0177019    1.258386
         11  |   .7538361   .3289382     2.29   0.022      .108964    1.398708
         12  |   .7733938   .3272777     2.36   0.018      .131777    1.415011
             |
       _cons |   53.00151   .2835907   186.89   0.000     52.44554    53.55748
------------------------------------------------------------------------------
```

```
. regress percentCorrect SB15 SB30 SByear i.day i.month

      Source |       SS       df       MS              Number of obs =    4748
-------------+------------------------------           F( 20,  4727) =   11.30
       Model |  3525.92639    20  176.296319           Prob > F      =  0.0000
    Residual |  73716.3054  4727  15.5947335           R-squared     =  0.0456
-------------+------------------------------           Adj R-squared =  0.0416
       Total |  77242.2318  4747  16.2717994           Root MSE      =   3.949

------------------------------------------------------------------------------
percentCor~t |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        SB15 |  -1.240136   2.053808    -0.60   0.546    -5.266557    2.786284
        SB30 |  -.7431278   1.425569    -0.52   0.602    -3.537907    2.051652
      SByear |  -2.592512    .219135   -11.83   0.000    -3.022119   -2.162905
             |
         day |
          1  |   .3913359   .2144947     1.82   0.068    -.0291736    .8118454
          2  |   1.239772   .2144956     5.78   0.000     .8192604    1.660283
          3  |   1.183859   .2144192     5.52   0.000     .7634971     1.60422
          4  |   1.085319   .2144192     5.06   0.000     .6649575    1.505681
          5  |   .9744364   .2144952     4.54   0.000     .5539258    1.394947
          6  |   .5588174   .2144932     2.61   0.009     .1383107    .9793241
             |
       month |
          2  |   .2453135   .2849388     0.86   0.389    -.3132994    .8039263
          3  |   .3771473   .2781999     1.36   0.175    -.1682542    .9225488
          4  |   .5237215   .2805069     1.87   0.062    -.0262027    1.073646
          5  |   .0104462   .2781974     0.04   0.970    -.5349503    .5558427
          6  |   .5289441   .2805084     1.89   0.059    -.0209832    1.078871
          7  |   .3302923   .2781974     1.19   0.235    -.2151042    .8756888
          8  |   .4852841   .2781999     1.74   0.081    -.0601174    1.030686
          9  |   .7921955   .2805074     2.82   0.005     .2422703    1.342121
         10  |   .5618306   .2781974     2.02   0.043     .0164341    1.107227
         11  |   .5554552   .2811745     1.98   0.048     .0042222    1.106688
         12  |   .4887522   .2797551     1.75   0.081    -.0596982    1.037203
             |
       _cons |   5.818174   .2424117    24.00   0.000     5.342935    6.293414
------------------------------------------------------------------------------
```

```
. regress Stopped SB15 SB30 SByear i.day i.month

      Source |       SS       df       MS              Number of obs =    5114
-------------+------------------------------           F( 20,  5093) =   31.87
       Model |   285419826    20  14270991.3           Prob > F      =  0.0000
    Residual |  2.2808e+09  5093  447828.956           R-squared     =  0.1112
-------------+------------------------------           Adj R-squared =  0.1077
       Total |  2.5662e+09  5113  501899.609           Root MSE      =   669.2

------------------------------------------------------------------------------
     Stopped |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        SB15 |  -152.0298   347.9161    -0.44   0.662     -834.095    530.0353
        SB30 |   222.4903   241.4106     0.92   0.357    -250.7782    695.7589
      SByear |   333.8645   37.02748     9.02   0.000     261.2748    406.4543
             |
         day |
          1  |  -76.78079   35.02961    -2.19   0.028    -145.4539   -8.107702
          2  |   218.4302   35.02969     6.24   0.000     149.7569    287.1034
          3  |   308.7846   35.01801     8.82   0.000     240.1342     377.435
          4  |    309.274   35.01813     8.83   0.000     240.6235    377.9246
          5  |   383.1177   35.01784    10.94   0.000     314.4677    451.7678
          6  |   293.0527   35.01751     8.37   0.000     224.4033    361.7021
             |
       month |
          2  |   67.38938   46.50569     1.45   0.147    -23.78176    158.5605
          3  |  -30.12305   45.42899    -0.66   0.507    -119.1834     58.9373
          4  |   -77.9748   45.80557    -1.70   0.089    -167.7734    11.82381
          5  |  -129.5103   45.42849    -2.85   0.004    -218.5697   -40.45094
          6  |  -253.7299   45.80594    -5.54   0.000    -343.5292   -163.9306
          7  |   -341.728   45.42842    -7.52   0.000    -430.7872   -252.6688
          8  |  -312.3172   45.42892    -6.87   0.000    -401.3774    -223.257
          9  |  -288.3414   45.80572    -6.29   0.000    -378.1403   -198.5425
         10  |  -210.1689   45.42842    -4.63   0.000    -299.2281   -121.1097
         11  |  -285.3618   45.90687    -6.22   0.000     -375.359   -195.3645
         12  |  -444.3315   45.66444    -9.73   0.000    -533.8535   -354.8096
             |
       _cons |   954.6169   39.55647    24.13   0.000     877.0692    1032.165
------------------------------------------------------------------------------
```

Figures 15-18 (left to right, top to bottom). Regressions for Sean Bell.

The pattern that these regressions show is exhibited in the regressions ran for Eric Garner and Freddie Gray's death as well, which can be found in the appendix. Due to the size of our dataset, almost all of the variables are statistically significant. When looking at the volume of stops, the change in stops is not statistically significant for our variables marking Sean Bell's death, except for until a year after. However, when considering the context of New York in 2006, the increase in the following year of stops was likely due to Bloomberg's advocation of the stop-and-frisk policy and the political pressure he placed on police to work towards "broken windows" policing.

When looking at our percentage regressions, yet again most values of the intervention variables we generated were not statistically significant. While some results may be statistically significant, they are not substantive, showing only one to two percent changes in black and white makeup of stops. When considering the volatility of our data, it is highly likely that these results simply indicate natural changes in stop-and-frisks. Therefore, we have concluded that there may be a small change in volume of stops after events, but there is no substantive change in the makeup of stop-and-frisks, indicating that these events did not impact who is stopped and frisked.

Discussion

The Constitutionality of Stop-and-Frisk Implementation in New York

In interpreting our results, we find that the 2013 court decision regarding New York's stop-and-frisk policy is substantiated and justified. As discussed in the Results and Analysis section, our findings show continual disproportionate stopping of Black and Hispanic populations across the entire time frame analyzed, though Asians almost never stopped. This is unsurprisingly consistent with the literature and court cases that assert a racial implementation of the stop-and-frisk policy. Across both genders, Blacks are stopped disproportionately higher as compared to other races. The gender effect is incredibly pronounced, with males being stopped much more than females, is shown in Figure 3. This could imply the role of unconscious bias in police officers making stops or could imply specific targeting of black and brown populations. Our results provide support for the idea that threshold for suspicion, how much it takes to consider a person a threat, is much lower for Black males than for under-targeted Asian females. This means that the implementation of stop-and-frisk perhaps does not guarantee equal protection against the law, if the practice unequally affects citizens. This racial disparity is also present in the percent of stops that become frisks as well. What is interesting is the increasing daily volatility of frisks after the 2013 court decision that found the NYPD's implementation unconstitutional. The increased volatility trends towards a less explicit racial bias in the practice of stop-and-frisk. This trend goes to further support Judge Sheindlin's ruling that stop-and-frisk is not unconstitutional itself but that the

NYPD’s implementation is. It shows that there may be a way for stop-and-frisk to exist without overt racial bias.

The effectiveness of the implementation of stop-and-frisk is hotly debated by politicians, police chiefs, and the public alike. If the implementation itself were effective, this means that the more searches conducted, more contraband would be found. Instead, we see an inverse relationship between the number of frisks and any contraband found, suggesting not only the unconstitutionality of the practice, but the incredible infectivity of it as well. It is important to note that as the number of frisks decreased after 2013, the percent of fruitful searches is on the rise, further corroborating the fundamental implementation idea that, simply, less is more. This dismantles the NYPD narrative that more stops lead to less crime and provides support for the opposite.

It is important to revisit the influences of the stop-and-frisk policy, namely the “broken windows” theory. Although we did not analyze reduction in crime specifically, we can attempt to extrapolate rates of crime reduction from the fruitful frisk rate. The practice is quite ineffective at high rates of frisks, dealing a blow to the idea that “maintaining an environment of order” with increasing police frisks does not yield less crime.

Generally speaking, stop-and-frisk in New York has been embittered with constitutionality and effectiveness issues. We have shown support for the critiques of the stop-and-frisk practice, but also interestingly show a trend towards achieving a more equitable implementation of the practice. There’s growth being made, but is clear that there is a lot of work to be done.

What Impacts New York's Implementation of Police Policy?

The lack of substantive change in the makeup of stops and frisks points to the idea that the deaths of the three men we looked at, regardless of political context or qualifying circumstances, did not impact the implementation of New York's stop-and-frisk policy. Due to the changes over time observed, it is more likely that social and political contexts impact the implementation of stop-and-frisk, such as the 2013 court decision that the policy of stop-and-frisk in New York City was unconstitutional. Individual events may work towards changing the greater socio-political climate that impacts police policy, but we can assume that individual events do not impact policy alone, unless indirectly, by leading to changes in the judicial system, which changes the implementation of policy in turn.

Our results are consistent with the claims acknowledged in the introduction, made by Jay Newberry: that police stop and frisks have both decreased, and effectiveness is increased. The increased effectiveness Newberry addresses is supported by evidence regarding increased arrests (2017, pp. 14). In our results, we see this effectiveness manifests as an increase in fruitful search rates, indicating that frisks are being conducted more often with reasonable suspicion. However, we also found a consistent proportion of stops as well as frisks for each race, pointing to a continuation of racial bias, whether conscious or unconscious, within implementation of stop and frisk policy. Though the daily percentages show more varying percentages, there is still a large difference between races on average. The increased variation shows that the changes in policy due to the 2013 court decision may have improved the racial inequality of stop-and-frisk to an extent, but it has not caused the elimination of inequality within stop-and-frisks in New York.

Based on the continued racial inequality, and lack of impact of the three events we chose, we can conclude that only larger structural and societal changes will impact policy with regard to stop-and-frisk. The increase in variation of racial percentages after the 2013 court decision points to the impact of the judicial system, but the relatively stagnant monthly percentages shows that the impact has yet to change the overall trend of racial disparities. Thought the volume of stops and frisks has changed dramatically in response to public outrage and judicial condemnation, it will take much longer to change the implicit and explicit racial biases embedded within our systems of justice.

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Tables and Figures

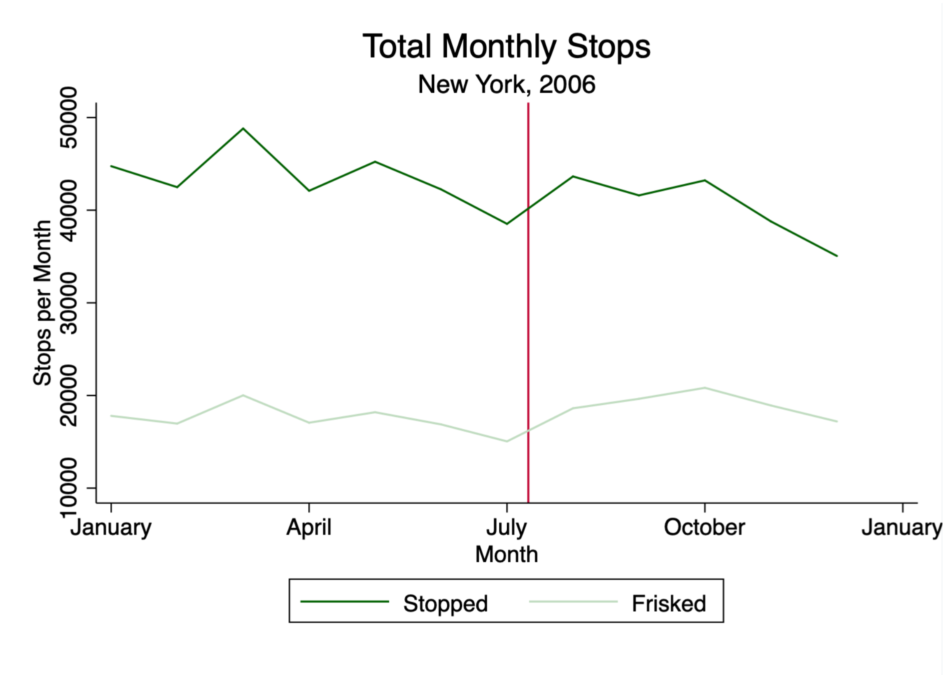

Figure 19. Monthly Stop Totals for 2006. This figure illustrates the general trend of stops in the year of Sean Bell's death (denoted by the red line).

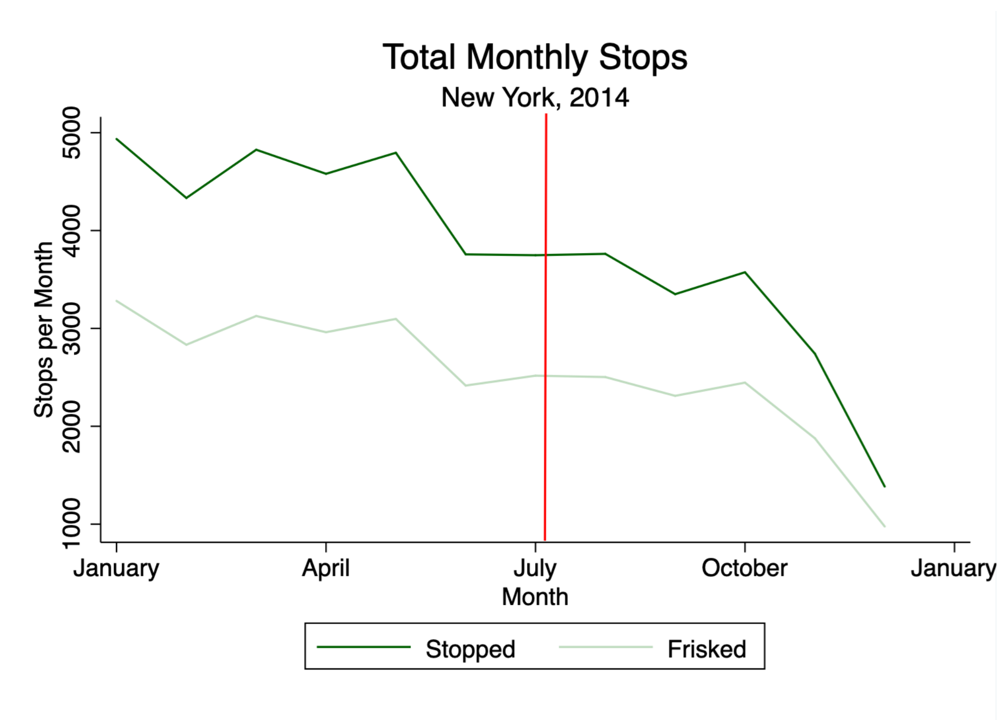

Figure 20. Monthly Stop Totals for 2014. This figure illustrates the general trend of stops in the year of Eric Garner's death (denoted by the red line).

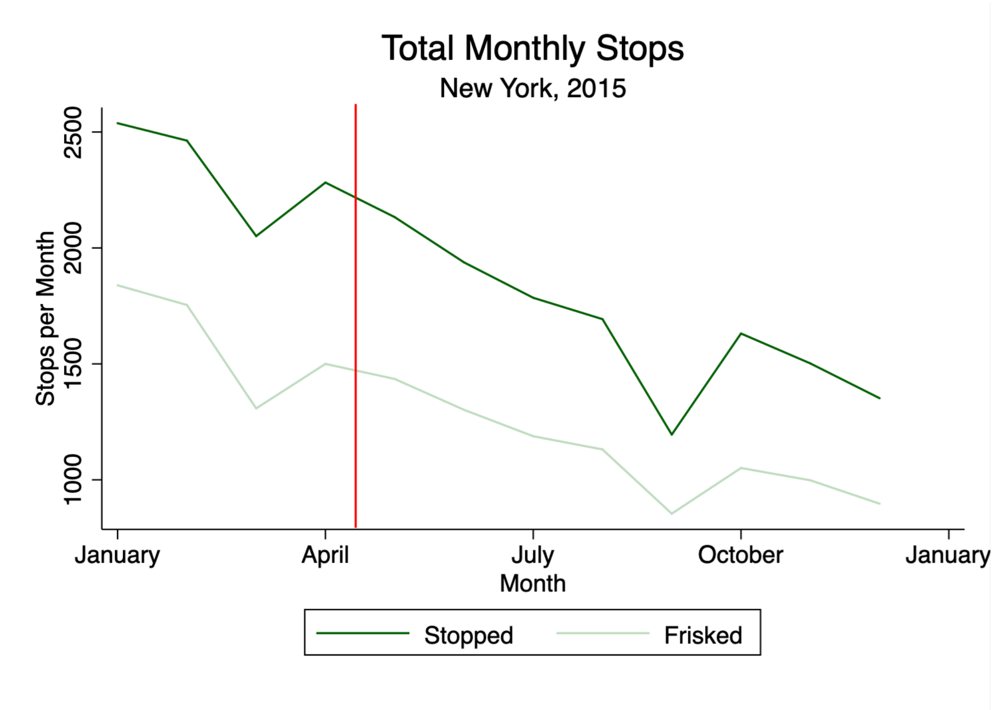

Figure 21. Monthly Stop Totals for 2015. This figure illustrates the general trend of stops in the year of Freddie Gray's death (denoted by the red line).

. regress percentWhite EG15 EG30 EGyear i.day i.month

Source	SS	df	MS
Model	3467.26203	20	173.363101
Residual	31189.5213	4727	6.59816401
Total	34656.7833	4747	7.30077593

Number of obs =	4748
F(20, 4727) =	26.27
Prob > F =	0.0000
R-squared =	0.1000
Adj R-squared =	0.0962
Root MSE =	2.5687

percentWhite	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
EG15	1.475565	1.329667	1.11	0.267	-1.131202	4.082333
EG30	-1.316701	.925458	-1.42	0.155	-3.13103	.4976281
EGyear	1.222236	.1425647	8.57	0.000	.9427427	1.501729
day						
1	.8208476	.1395136	5.88	0.000	.547336	1.094359
2	1.982009	.1395144	14.21	0.000	1.708496	2.255523
3	1.984234	.1394644	14.23	0.000	1.710818	2.257649
4	1.904973	.1394647	13.66	0.000	1.631558	2.178389
5	1.223552	.1395207	8.77	0.000	.950026	1.497077
6	.6476181	.1395132	4.64	0.000	.3741071	.9211291
month						
2	.5705425	.1853421	3.08	0.002	.2071855	.9338995
3	1.206822	.1809588	6.67	0.000	.8520582	1.561585
4	.9418486	.1824593	5.16	0.000	.5841433	1.299554
5	.9530057	.1809571	5.27	0.000	.5982455	1.307766
6	.9493216	.1824604	5.20	0.000	.5916143	1.307029
7	.9964429	.1825261	5.46	0.000	.6386066	1.354279
8	.7072521	.1809733	3.91	0.000	.3524601	1.062044
9	.7030903	.1824597	3.85	0.000	.3453843	1.060796
10	.4843503	.1809571	2.68	0.007	.1295901	.8391105
11	.246869	.18246	1.35	0.176	-.1108377	.6045756
12	.5141745	.1809581	2.84	0.005	.1594124	.8689367
_cons	8.271203	.1576748	52.46	0.000	7.962087	8.58032

. regress percentBlack EG15 EG30 EGyear i.day i.month

Source	SS	df	MS
Model	7553.40761	20	377.67038
Residual	100334.123	4727	21.2257506
Total	107887.53	4747	22.7275185

Number of obs =	4748
F(20, 4727) =	17.79
Prob > F =	0.0000
R-squared =	0.0700
Adj R-squared =	0.0661
Root MSE =	4.6071

percentBlack	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
EG15	-1.491258	2.38486	-0.63	0.532	-6.166695	3.184179
EG30	2.825289	1.65988	1.70	0.089	-.4288494	6.079427
EGyear	1.210482	.2557008	4.73	0.000	.7091889	1.711774
day						
1	-.4659587	.2502284	-1.86	0.063	-.9565229	.0246055
2	-1.799374	.2502298	-7.19	0.000	-2.289941	-1.308807
3	-1.856406	.2501401	-7.42	0.000	-2.346797	-1.366015
4	-1.811212	.2501406	-7.24	0.000	-2.301604	-1.32082
5	-1.332668	.2502411	-5.33	0.000	-1.823257	-.8420784
6	-.1714342	.2502277	-0.69	0.493	-.6619971	.3191288
month						
2	-1.27692	.3324254	-3.84	0.000	-1.928629	-.6252116
3	-1.864909	.3245634	-5.75	0.000	-2.501204	-1.228613
4	-.9960507	.3272548	-3.04	0.002	-1.637623	-.3544788
5	-.4710405	.3245604	-1.45	0.147	-1.10733	.1652492
6	-.2659335	.3272567	-0.81	0.416	-.907509	.375642
7	.633299	.3273747	1.93	0.053	-.0085079	1.275106
8	1.099752	.3245895	3.39	0.001	.4634052	1.736099
9	.8412816	.3272554	2.57	0.010	.1997084	1.482855
10	.6203572	.3245604	1.91	0.056	-.0159325	1.256647
11	.7740539	.327256	2.37	0.018	.1324795	1.415628
12	.8408093	.3245622	2.59	0.010	.2045161	1.477103
_cons	52.90059	.2828019	187.06	0.000	52.34616	53.45501

. regress percentCorrect EG15 EG30 EGyear i.day i.month

Source	SS	df	MS
Model	7151.75535	20	357.587768
Residual	70090.4764	4727	14.827687
Total	77242.2318	4747	16.2717994

Number of obs =	4748
F(20, 4727) =	24.12
Prob > F =	0.0000
R-squared =	0.0926
Adj R-squared =	0.0887
Root MSE =	3.8507

percentCor~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
EG15	1.676365	1.993279	0.84	0.400	-2.231391	5.58412
EG30	-6.503987	1.387337	-4.69	0.000	-9.223813	-3.784161
EGyear	4.28925	.2137161	20.07	0.000	3.870267	4.708233
day						
1	.3927621	.2091422	1.88	0.060	-.0172541	.8027783
2	1.244497	.2091434	5.95	0.000	.8344781	1.654515
3	1.189344	.2090685	5.69	0.000	.7794723	1.599215
4	1.090524	.2090689	5.22	0.000	.6806516	1.500396
5	.9823141	.2091529	4.70	0.000	.572277	1.392351
6	.5574302	.2091417	2.67	0.008	.147415	.9674453
month						
2	.2496404	.2778429	0.90	0.369	-.2950612	.794342
3	.3771935	.2712719	1.39	0.164	-.1546258	.9090127
4	.5236993	.2735214	1.91	0.056	-.01253	1.059929
5	.0104761	.2712694	0.04	0.969	-.5213383	.5422905
6	.5289622	.2735229	1.93	0.053	-.0072701	1.065194
7	.5164507	.2736215	1.89	0.059	-.019975	1.052876
8	.5014582	.2712937	1.85	0.065	-.0304038	1.03332
9	.7921918	.2735219	2.90	0.004	.2559615	1.328422
10	.5618221	.2712694	2.07	0.038	.0300077	1.093636
11	.5234206	.2735224	1.91	0.056	-.0128107	1.059652
12	.4641443	.2712709	1.71	0.087	-.0676729	.9959616
_cons	5.285466	.2363674	22.36	0.000	4.822076	5.748856

. regress Stopped EG15 EG30 EGyear i.day i.month

Source	SS	df	MS
Model	569466832	20	28473341.6
Residual	1.9967e+09	5093	392056.915
Total	2.5662e+09	5113	501899.609

Number of obs =	5114
F(20, 5093) =	72.63
Prob > F =	0.0000
R-squared =	0.2219
Adj R-squared =	0.2189
Root MSE =	626.14

Stopped	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
EG15	39.06322	324.1158	0.12	0.904	-596.3431	674.4696
EG30	168.8176	225.4647	0.75	0.454	-273.1901	610.8253
EGyear	-983.0036	34.65094	-28.37	0.000	-1050.934	-915.0729
day						
1	-77.10595	32.77427	-2.35	0.019	-141.3576	-12.85429
2	217.654	32.77437	6.64	0.000	153.4022	281.9059
3	307.8779	32.76339	9.40	0.000	243.6475	372.1082
4	308.3724	32.7635	9.41	0.000	244.1419	372.603
5	383.3384	32.76467	11.70	0.000	319.1055	447.5712
6	293.4955	32.76301	8.96	0.000	229.266	357.7251
month						
2	66.44265	43.51356	1.53	0.127	-18.86262	151.7479
3	-30.11542	42.50613	-0.71	0.479	-113.4457	53.21487
4	-77.96986	42.85848	-1.82	0.069	-161.9909	6.051182
5	-129.5114	42.50566	-3.05	0.002	-212.8408	-46.18206
6	-253.7213	42.85882	-5.92	0.000	-337.743	-169.6996
7	-345.5346	42.84716	-8.06	0.000	-429.5335	-261.5358
8	-312.7055	42.50924	-7.36	0.000	-396.0419	-229.3691
9	-288.3323	42.85862	-6.73	0.000	-372.3536	-204.311
10	-210.1699	42.50559	-4.94	0.000	-293.4992	-126.8407
11	-283.7237	42.85875	-6.62	0.000	-367.7453	-199.7021
12	-439.8974	42.50586	-10.35	0.000	-523.2272	-356.5676
_cons	1048.996	37.01043	28.34	0.000	976.4393	1121.552

Figures 22-25 (left to right, top to bottom). Regressions for Eric Garner.

. regress percentWhite FG15 FG30 FGyear i.day i.month

Source	SS	df	MS
Model	3021.78977	20	151.089489
Residual	31634.9936	4727	6.69240397
Total	34656.7833	4747	7.30077593

Number of obs =	4748
F(20, 4727) =	22.58
Prob > F =	0.0000
R-squared =	0.0872
Adj R-squared =	0.0833
Root MSE =	2.587

percentWhite	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FG15	2.619453	1.385064	1.89	0.059	-.0959187	5.334824
FG30	-1.616732	.9965214	-1.62	0.105	-3.570379	.3369139
FGyear	.3516877	.1730097	2.03	0.042	.0125081	.6908673
day						
1	.8203155	.1405066	5.84	0.000	.544857	1.095774
2	1.981539	.1405074	14.10	0.000	1.70608	2.256999
3	1.983661	.1404571	14.12	0.000	1.7083	2.259023
4	1.904368	.1404573	13.56	0.000	1.629006	2.17973
5	1.223449	.1405072	8.71	0.000	.9479898	1.498909
6	.6493971	.1405059	4.62	0.000	.3739401	.9248541
month						
2	.5697771	.186661	3.05	0.002	.2038345	.9357197
3	1.206822	.1822465	6.62	0.000	.849534	1.56411
4	.9305205	.184894	5.03	0.000	.5680421	1.292999
5	.9379807	.1827897	5.13	0.000	.5796276	1.296334
6	.922275	.18424	5.01	0.000	.5610788	1.283471
7	.9523172	.18273	5.21	0.000	.5940812	1.310553
8	.6769288	.1827318	3.70	0.000	.3186893	1.035168
9	.6760452	.1842392	3.67	0.000	.3148504	1.03724
10	.4572964	.1827301	2.50	0.012	.0990602	.8155326
11	.219815	.1842397	1.19	0.233	-.1413807	.5810107
12	.4871296	.1827309	2.67	0.008	.1288919	.8453674
_cons	8.365292	.1584144	52.81	0.000	8.054726	8.675857

. regress percentBlack FG15 FG30 FGyear i.day i.month

Source	SS	df	MS
Model	7683.36432	20	384.168216
Residual	100204.166	4727	21.1982581
Total	107887.53	4747	22.7275185

Number of obs =	4748
F(20, 4727) =	18.12
Prob > F =	0.0000
R-squared =	0.0712
Adj R-squared =	0.0673
Root MSE =	4.6042

percentBlack	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FG15	-4.05133	2.465068	-1.64	0.100	-8.884013	.7813526
FG30	-.1982765	1.773559	-0.11	0.911	-3.675278	3.278725
FGyear	1.784063	.307914	5.79	0.000	1.180408	2.387718
day						
1	-.468468	.2500667	-1.87	0.061	-.9587151	.0217792
2	-1.802137	.2500681	-7.21	0.000	-2.292387	-1.311887
3	-1.85934	.2499785	-7.44	0.000	-2.349414	-1.369265
4	-1.81421	.2499789	-7.26	0.000	-2.304286	-1.324135
5	-1.326857	.2500676	-5.31	0.000	-1.817106	-.8366078
6	-.1696417	.2500653	-0.68	0.498	-.6598863	.3206029
month						
2	-1.277684	.33221	-3.85	0.000	-1.928971	-.6263979
3	-1.864875	.3243532	-5.75	0.000	-2.500759	-1.228992
4	-.9680445	.3290651	-2.94	0.003	-1.613165	-.3229236
5	-.6068193	.3253201	-1.87	0.062	-1.244598	.0309596
6	-.4031391	.3279011	-1.23	0.219	-1.045978	.2396998
7	.5713257	.3252138	1.76	0.079	-.0662449	1.208896
8	.9695109	.325217	2.98	0.003	.3319341	1.607088
9	.7040843	.3278998	2.15	0.032	.0612479	1.346921
10	.4831001	.3252139	1.49	0.137	-.1544707	1.120671
11	.6368297	.3279007	1.94	0.052	-.0060084	1.279668
12	.7036128	.3252154	2.16	0.031	.0660391	1.341187
_cons	52.99421	.281938	187.96	0.000	52.44148	53.54694

. regress percentCorrect FG15 FG30 FGyear i.day i.month

Source	SS	df	MS
Model	19701.9062	20	985.095311
Residual	57540.3256	4727	12.1726942
Total	77242.2318	4747	16.2717994

Number of obs =	4748
F(20, 4727) =	80.93
Prob > F =	0.0000
R-squared =	0.2551
Adj R-squared =	0.2519
Root MSE =	3.4889

percentCor~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FG15	-.9393114	1.86798	-0.50	0.615	-4.601423	2.7228
FG30	-2.008424	1.343968	-1.49	0.135	-4.643227	.6263794
FGyear	8.976867	.2333311	38.47	0.000	8.51943	9.434305
day						
1	.3792408	.1894956	2.00	0.045	.0077412	.7507404
2	1.231765	.1894966	6.50	0.000	.8602636	1.603267
3	1.176426	.1894287	6.21	0.000	.8050571	1.547794
4	1.077544	.1894291	5.69	0.000	.7061747	1.448913
5	.9795631	.1894963	5.17	0.000	.608062	1.351064
6	.5637066	.1894946	2.97	0.003	.192209	.9352043
month						
2	.2469425	.2517422	0.98	0.327	-.2465894	.7404744
3	.3772141	.2457884	1.53	0.125	-.1046457	.8590739
4	.3440763	.249359	1.38	0.168	-.1447835	.8329362
5	-.6651809	.2465211	-2.70	0.007	-1.148477	-.1818847
6	-.1615068	.248477	-0.65	0.516	-.6486374	.3256239
7	-.3602156	.2464406	-1.46	0.144	-.8433539	.1229228
8	-.205272	.246443	-0.83	0.405	-.6884152	.2778711
9	.1017542	.248476	0.41	0.682	-.3853746	.5888829
10	-.1287311	.2464407	-0.52	0.601	-.6118697	.3544075
11	-.1671322	.2484766	-0.67	0.501	-.6542622	.3199978
12	-.2262781	.2464418	-0.92	0.359	-.7094189	.2568626
_cons	5.622342	.213647	26.32	0.000	5.203494	6.041189

. regress Stopped FG15 FG30 FGyear i.day i.month

Source	SS	df	MS
Model	591919275	20	29595963.8
Residual	1.9743e+09	5093	387648.424
Total	2.5662e+09	5113	501899.609

Number of obs =	5114
F(20, 5093) =	76.35
Prob > F =	0.0000
R-squared =	0.2307
Adj R-squared =	0.2276
Root MSE =	622.61

Stopped	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FG15	-20.98257	333.3067	-0.06	0.950	-674.4069	632.4418
FG30	-75.90253	238.5739	-0.32	0.750	-543.61	391.8049
FGyear	-1007.19	34.45434	-29.23	0.000	-1074.735	-939.6446
day						
1	-75.71501	32.58951	-2.32	0.020	-139.6045	-11.82555
2	217.6588	32.58959	6.68	0.000	153.7692	281.5484
3	307.8782	32.57867	9.45	0.000	244.01	371.7464
4	308.3704	32.57877	9.47	0.000	244.502	372.2388
5	382.2181	32.57857	11.73	0.000	318.3501	446.0861
6	292.1522	32.57825	8.97	0.000	228.2849	356.0196
month						
2	68.95748	43.26826	1.59	0.111	-15.8669	153.7819
3	-30.13269	42.26647	-0.71	0.476	-112.9931	52.72776
4	-78.03322	42.87149	-1.82	0.069	-162.0798	6.01333
5	-128.9926	42.29817	-3.05	0.002	-211.9151	-46.06997
6	-253.7394	42.61718	-5.95	0.000	-337.2874	-170.1914
7	-341.7237	42.26594	-8.09	0.000	-424.5831	-258.8643
8	-312.3286	42.2664	-7.39	0.000	-395.189	-229.4683
9	-288.3444	42.61697	-6.77	0.000	-371.892	-204.7968
10	-210.1731	42.26594	-4.97	0.000	-293.0325	-127.3137
11	-283.7353	42.61711	-6.66	0.000	-367.2832	-200.1874
12	-439.9063	42.2662	-10.41	0.000	-522.7662	-357.0464
_cons	1050.885	36.80169	28.56	0.000	978.7378	1123.032

Figures 26-29 (left to right, top to bottom). Regressions for Freddie Gray.