IDENTIFYING EFFECTIVE INVESTIGATIVE PRACTICES: A NATIONAL STUDY USING TRAJECTORY ANALYSIS

Trajectories of U.S. Crime Clearance Rates

[PHASE I REPORT]

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Introduction and Overview of the Project

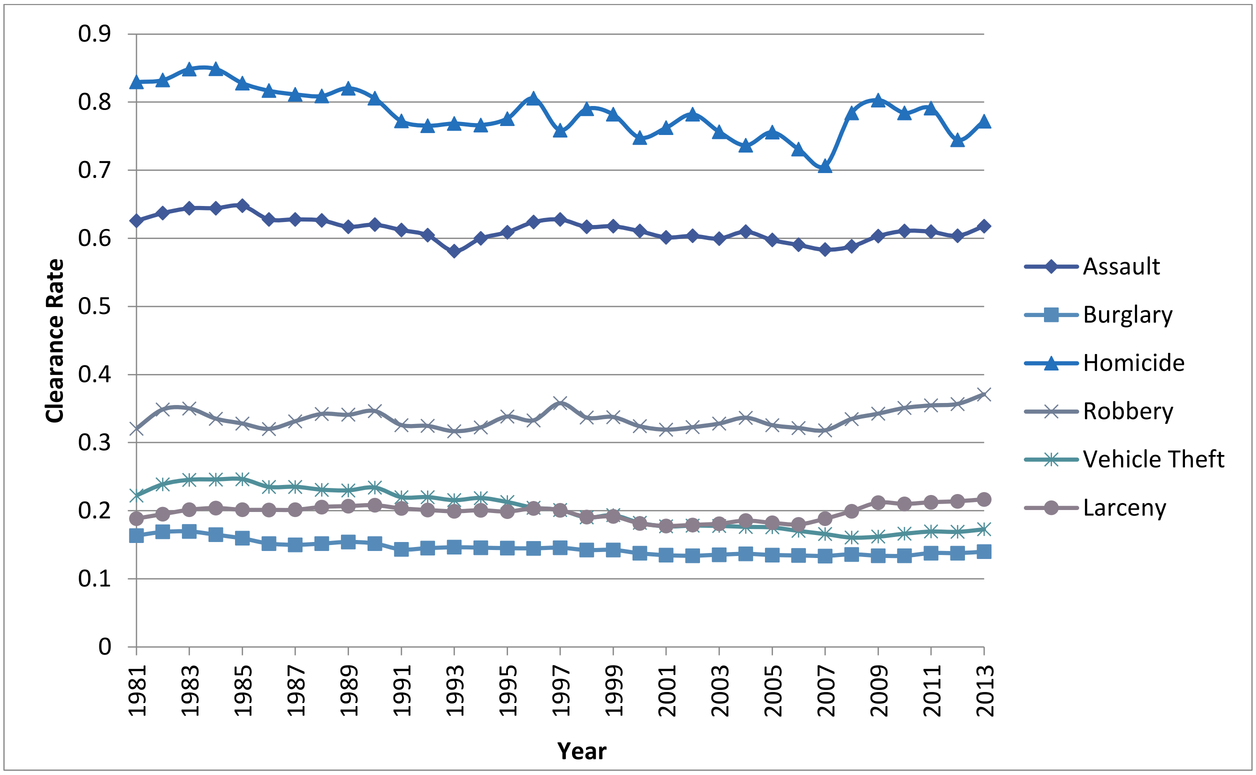
One of the most important functions of law enforcement is the investigation and resolution of crimes. In the last half century, American police agencies have seen a great deal of advancement and innovation in criminal investigations, starting with the standardization and computer automation of case documentation and processing to improvements in forensics and investigations technologies to identify suspects more accurately and quickly. Crime analysts have also become an important part of investigations, assisting with searching for individuals, gathering clues, and generating patterns of similarities between cases. Particularly for serious victimizations involving violence and theft, police agencies devote significant amounts of resources, often 10-20% of their annual budgets.

Despite these recent advances and despite the resources allocated to investigations, the resolution or clearance of crime in the United States is arguably low. In the latest year for which data are available in the United States (2014), there were approximately 1.08 million violent crimes reported to the police, of which 53% were *not* cleared by an arrest or exceptional means, including 4,572 homicides.[1] In addition, of the 7.5 million serious property crimes that occurred in 2014, almost 6 million remained unsolved (about 80%). In total, this amounts to approximately 76% of all serious crimes that did not result in a resolution of a crime.

Perhaps even more provocative is that these clearance rates have not changed much over the years for many crime types (Braga et al., 2011). For example, in our analysis, we examined yearly clearances for homicide, robbery, aggravated assaults, burglary, vehicle theft and larceny as a proportion of the number of those crimes per year for all U.S. agencies with 100 or more officers. As Figure 1 illustrates, from 1981 through 2013, clearance rates for aggravated assaults have hovered around 60%; robbery in the 32-38% range; and burglary staying relatively stable between 14-15%. Clearance rates for vehicle theft and larceny have slightly declined or increased, respectively, but average around 20%. Homicide clearances for all agencies nationwide have been on the decline from the 1960s, from 92% to 65% today (see Cronin et al., 2007). We see a similarly downward trend in our data.

[1] See Crime in the United States-2014, at https://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2014/crime-in-the-u.s.-2014/offenses-known-to-law-enforcement/clearances/main.

Figure 1. Yearly crime clearance rates for the United States from 1981-2013 (all agencies with 100 or more officers)



The stability of crime clearance rates over extended periods of time as well as the significant decline in homicide clearance since the 1960s raises questions about what might be causing these low, stable, and/or declining clearance rates and whether the police can do anything to improve this situation. While it is likely that agencies mimic these national trends, there may be variations that are masked by these nationwide clearance rate trends. It is possible that some law enforcement organizations may be better at clearing crime than others; perhaps due to better use of technologies, investigative techniques, policies, best practices, and/or resources expended. Or, maybe agencies are very similar, and there are just “natural” rates of clearance for particular types of crimes that explain these stable nationwide averages.

Current research on crime clearances leaves many of these questions unanswered (Braga et al., 2011; Wellford and Alexander, 2015). In fact, there is little research on the link between the efficacy or effectiveness of investigations and crime clearance rates. Researchers are much more likely to conduct evaluations on patrol operations. For example, the Lum, Koper, and Telep Matrix[2] now houses 146 moderate to very strong evaluation studies of policing. However, less than 10 seem connected to the work of investigative units, and those units are unusually involved in some kind of problem-oriented project rather than traditional investigative practices (see, e.g., Bynum and Varano, 2003; Eck and Wartell, 1998Jolin et al., 1998; Koper et al., 2013; Martin and Sherman, 1986; Nunn et al., 2006; Spergel et al., 2002). Indeed, the investigative function has been largely detached from recent innovations in policing and police research, such as community policing, problem-oriented policing, or hot spots policing, all which has been connected to crime prevention.

The research we do have on investigations tends to focus not on the outcome of investigative practices and their contribution to crime deterrence, prevention or reduction, but more on the impact of investigative practices on clearances of individual cases. For example, groundbreaking research conducted during the 1970s and 1980s by the RAND Corporation and others raised questions about the utility of investigations by showing that the outcomes of criminal investigations typically depend on information obtained by patrol officers who first respond to the scene, and that follow-up activities by detectives appeared to add little to the apprehension of offenders (Greenwood and Petersilia, 1975). Horvath et al. (2001) also found that the process and management of criminal investigations have changed little over the last several decades.

Concern over the ability of police investigations to impact crime rates and crime clearances led researchers to examine ways to improve criminal investigations through better management, training, policies, and investigative techniques (e.g., Cronin et al., 2007; Eck, 1983; Wellford and Cronin, 1999). There has also been growth in the use of data systems, crime analysis, and forensic techniques that might help improve investigations (e.g., see Danziger and Kraemer, 1985; Roman et al., 2008; Zaworski, 2004). Researchers are just beginning to learn more about the effectiveness of these efforts in improving investigations.

The bottom line is that we know little about whether specific investigative techniques or an agency's investigative policies impact crime clearances and in turn, crime rates. However, understanding what causes trends of case clearances in police agencies is important, and not only because a significant amount of police resources are spent on investigations. Investigations have symbolic and operational significance in both law enforcement circles and society. Investigations and clearance of crime incidents through arrest is one of the defining mainstays of American policing and occurs not just in investigative units, but also across patrol and

[2] See Lum et al. (2011) and also http://cebcp.org/evidence-based-policing/the-matrix/.

specialized units. Citizens and politicians judge the police in large part by their ability to solve cases, and high-profile cases often make the news. One only needs to attend Compstat or managerial meetings to see that police executives are frequently concerned about the status of unsolved, high-profile cases. In surveys of police executives, improving investigations was consistently identified as a research priority (IACP 2008).

Perhaps most important is that unsolved crimes cluster in those communities that also often have the lowest levels of support for law enforcement. Low clearance rates in communities already suffering from high rates of crime could reflect—or contribute to—the lack of trust, confidence, cooperation, or support and support for law enforcement in those communities (Carter, 2013). Fortunately, improving the speed in which police resolve cases is something that both law enforcement and citizens value. Understanding why rates are both low and don't seem to change over time (or perhaps get worse), and whether this situation can be improved, is critical in delivering high-quality police service to communities.

Given the importance of improving our understanding of investigative clearance, we aim to better understand variations in clearance rate trends amongst individual law enforcement agencies and whether they follow or deviate from national trends. Our plan is to use what we anticipate are natural variations in clearance rate trends across agencies to identify a sample of agencies that differ in clearance patterns but are similar in crime levels, and then to examine organizational practices to explore why some agencies perform better that others. Toward this end, this project consists of three phases:

Phase I: A national trajectory analysis of case clearance data. This phase includes determining whether there are unique "trajectories" or groups of longitudinal patterns of clearance rates for individual agencies that may be masked by the national trends described above. We examine the clearance rates from 1981 – to 2013 for U.S. law enforcement agencies with over 100 officers, and also a subset of this sample, the 100 largest agencies (as determined in 1980, the start of our analysis). We then conduct dual trajectory analysis on the 100 largest agencies to understand the relationship between these clearance rate trajectories and crime rates. In later analysis we will examine other factors that might contribute to these trajectories.

Phase II: Conduct focus groups with police agencies to better understand case clearance trajectories. Once we identify trajectories of case clearances for individual agencies for specific crime types, we will select a representative sample of agencies in which to conduct more in-depth examination. Categorizing agencies with regard to their long-term clearance rates will allow us to further survey and analyze smaller samples of agencies and what might contribute to their clearance rate trends over time. For example, we might group agencies into "high performers" (consistently above-average clearance rate trajectories over time compared to others), "improvers" (over time have significantly improved in their clearance compared to national trends), "low performers" (consistently below-average clearance rates over time) or "decliners" (those who have consistent declines in their clearance rates over time compared to the national average). Why do some agencies worsen in their clearance rates when the general trend is stable or even improving? Perhaps there might be changes in reporting at the agency level that might explain these patterns, or perhaps real changes in investigative techniques, technologies, or policies over time have had an impact. In order to better understand these phenomena, we propose to conduct interviews and focus groups of relevant personnel from small sub-samples of different trajectory groups as describe above.

Phase III: Conduct case analysis at four agencies with significantly increasing and decreasing crime clearance trajectories. Finally, we will identify four agencies to examine investigative cases and processes more carefully who evidence significant improvements in their clearance or who have worsening clearance rates over time. In these in-depth case studies, we will select particular crime types to study based on our trajectory and organizational analysis, to examine the nature of these agencies' cases. We will select samples of open and closed case files, and by using standardized data collection instruments, we will describe case characteristics and the investigative practices and resources applied in each case. This will allow us to determine the role the specific practices used by police contribute to clearance. In addition, we will collect information about agency policies and resources that are thought to account for clearance trends. We will also interview staff responsible for the cases/crime types to seek their explanations of why a case was cleared or not or why we see a particular trend during our analysis. Finally, we will collect information on the demographic, economic and social context of the area where each offense occurred. It is this phase of the research that will allow us to make specific recommendations to agencies on how they might improve clearance in ways that are just (i.e., minimize false arrests) and respectful (i.e., increase community support for police).

In this report, we present the results of Phase I.

Identifying Trends of Clearance Rates across U.S. Agencies

As Figure 1 illustrated, the proportion of crimes cleared in the United States for serious crimes of homicide, robbery, aggravated assault, burglary, vehicle theft and larceny have been relatively stable—or in the case of homicide, declining—since the 1980s (see also Braga et al., 2011). Due to this stability, Braga et al. (2011) suggest that improvements in investigative techniques and resources may not appear to have translated into an increased probability of arrest for offenders (p. 8). But these proportions reflect the total clearance across thousands of agencies. Perhaps these national averages might mask important differences across agencies in their clearance rates and across different crime types within those agencies. It is likely that just like clearance rates themselves, these improvements might vary substantially at the agency level. To determine variations in clearance rate trends across U.S. agencies that might be masked by national averages, we use a technique known as trajectory analysis.

A. Trajectory Analysis for Crime Clearances

Trajectory analysis is a group-based modeling technique that allows for longitudinal data for large numbers of units of analysis (see Jones, Nagin, & Roeder, 2001; Nagin, 1999, 2005; Nagin and Land, 1993). Trajectory analysis is often used for exploratory analysis and to develop hypotheses to explain differences across certain groups (Nagin, 2005). For example, trajectory analysis has been used in developmental criminology to examine how large samples of individuals might be grouped according to their different offending patterns over their life course. Weisburd et al. (2004) used trajectory analysis to group crime trends across thousands of street segments over a fourteen year period into discernible longitudinal trends. In our study, we use trajectory analysis to categorize hundreds of police agencies, each with their own longitudinal trends of crime clearance, into a manageable number of clearance rate patterns. The use of trajectory analysis for analyzing national crime clearance data is innovative. By grouping clearance rate trends of individual agencies into a manageable number of similar trends, we may see variations from the overall nationwide (stable) trends. This aids in seeing the variations in agency clearance rate trends, easily identifying agencies for further study, and exploring whether other characteristics predict an agency's membership in any given trajectory grouping.

Group-based trajectory analysis is based on a semiparametric, group-based modeling strategy, and is similar to hierarchical modeling and latent growth curve modeling (see Jones et al., 2001). It is a finite mixture modeling application that uses trajectory groups to hypothesize about unknown subgroups in the population without assuming any particular population distribution (Nagin and Odgers, 2010). Two statistical criteria are used to model the best fit of data to a particular n-group solution: the Bayesian information criterion (BIC) and the Akaike information criterion (AIC), which tend to improve when more trajectory groups are added to a particular solution. Deciding what number of trajectory groups is adequate requires not only examining the BIC and AIC, but using other probability criteria and time-intensive exploratory techniques which we employ in our analysis (see Nagin, 2005).

B. Clearance Data and Sample

We estimated clearance rate trajectories for homicide, robbery, aggravated assaults, burglary, vehicle theft and larceny for all U.S. agencies with 100 or more officers, as well as the 100 largest agencies in the U.S. within this sample. The data used in this study derives from the "Offenses Known and Clearances by Arrest" summary data as reported to the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCP) program.[3] The UCR program is a nation-wide statistical compilation of crime reporting and clearance data that is produced from data received from over 18,000 city, university or college, county, state, tribal, and federal law enforcement agencies voluntarily participating in the program. Each year it asks agencies to submit the total number of reported crimes (in various categories) and also the total number of offenses cleared by arrest or exceptional means. It is important to note that an agency can report a crime as "cleared" in 2014 that occurred in 2005, for example, but that number is counted as a 2014 clearance in the UCR.

Because we are interested understanding long-term patterns of clearance rates across agencies, we analyze 32 years of clearance rates from 1981 through 2013 for those agencies with law enforcement functions that had 100 or more full-time authorized sworn officers, as determined by the Law Enforcement Management and Administrative Statistics (LEMAS) survey (2007). In our initial proposal, we decided to limit our analysis to agencies with 100 or more officers as well as clearance rates after 1980 for two practical reasons. Prior to 1981, many agencies in the UCR did not appear to have clearance rate statistics available, and agencies

[3] Due to the lengthy time period of data needed, the UCR data was obtained from the Inter-university Consortium for Political and Social Research (ICPSR) website (http://www.icpsr.umich.edu/).

smaller than 100 officers often did not report arrest rates for specific crimes or had 0 clearances to report. (We return to this issue shortly in our discussion of "Missing Data".) Using the "100 or more officers" threshold, 903 agencies fell within our purview. As we were also interested in the clearance rates of those agencies with the most crime, we also sharpened our focus to a smaller subset of this sample—the largest 100 agencies as determined by their size at the beginning of our time series (1980).

UCR presents counts of crime and clearance for 1981 – 2013 in yearly datasets disaggregated by month, per year, for each crime type. To conduct trajectory analysis we compiled this data into yearly clearance rates by summing the data across all months for each year, for each agency, and for each crime type. We defined the clearance rate of any given crime as the total number of clearances for that year divided by the total numbers of crimes for that year. We did this separately for homicide, robbery, burglary, vehicle theft and larceny. For aggravated assaults, because the UCR collects all assaults (both misdemeanor/minor and felonious/aggravated), we parsed out only categories of aggravated assaults ("gun assault," "knife assault," "other weapon assault," and "hand/feet assault") to create clearance rates for aggravated assaults. This process produced 32 annual clearance rates (1981-2013) for each of the six crime types we were interested in, and for 903 agencies in our sample.

C. Missing Data Analysis

Before conducting the trajectory analysis, we needed to resolve the issue of missing data within the UCR data. While trajectory analysis is not overly sensitive to some missing data, substantial amounts of missing data over consecutive years can cause analytic problems. Missing clearance information could manifest in the UCR data in various forms. For example, in any given year, Agency "A" may choose not to report its robbery occurrences to the UCR. Or, it may report its robberies, but not report the number of robberies cleared by arrest or exceptional means. Another possibility is that Agency A may report its robberies, but have a year in which it did not clear a single robbery case. Agency A could also have a year when it had zero robberies, but cleared 2 robberies from previous years (which UCR counts as 2 robbery clearances for the current year). While each of these situations are substantively different, the UCR does not indicate the nature of a missing value of crime or clearance. A missing value for clearance rate data derived from the UCR could, therefore, equal zero, be undefined (as in the case of 2 robberies cleared but no robberies occurring) or, it could simply be unreported.

Because of this, we could not assume that the clearance rate for robbery for Agency "A" in which no value appeared in that cell was either zero or unknown.

This problem compounds given the multi-year nature of our dataset. After calculating the proportion of crimes cleared for each agency and for each crime type and each year, missing data problems existed throughout the data in very few discernible patterns. In some agencies, data might be missing for a few years of the 32 years collected, sometimes consecutively and sometimes not. To deal with this problem, we made the following decisions. First, we deleted all agencies from Illinois due to their historically extensive missing data in the UCR. We also decided to remove all agencies classified as state highway patrol, given our interest in local jurisdictions. This reduced the sample size of agencies with 100 or more officers to 836. Florida also had extensive missing data in its aggravated assault data, so we deleted Florida agencies from only the aggravated assault data. After consulting with trajectory modeling experts on the missing data issue, we further eliminated agencies with 10 or more years of missing data as well as agencies with seven or more consecutive years of missing data for each crime type. After our deletions, the final sample of agencies for each crime type of interest is shown in Figure 2.

Figure 2. Final Sample of Agencies Examined for Each Crime Type

Crime Type	Full sample (agencies with 100 or more officers)	Smaller subsample (largest 100 agencies)
Homicide	519	92
Robbery	729	92
Aggravated Assault	673	86
Burglary	757	92
Vehicle theft	749	92
Larceny	729	91

We also noticed outliers after analyzing descriptive statistics across our data which appear to be input errors. For example, the number of clearances for one year for one agency was marked as "999" in the UCR raw data, whereas in previous and future months, clearance numbers were less than 10. We decided to change that year of clearance for that agency "missing."[4] These adjustments did not change the final number of cases in the sample.

[4] This included 3 agencies in the assault data in 1993, 1 agency in vehicle theft in 1984 and 1 agency in the robbery data for 1993.

In the next section, we report our trajectory analysis findings for each crime type for the total sample as described in Figure 2.

Trajectory Analysis Results

As described above, trajectory analysis allows researchers to group longitudinal patterns of a large sample into a manageable number of trends. Below, we conduct trajectory analysis on the data we constructed from the UCR for six crime types – homicide, robbery, aggravated assaults, burglary, vehicle theft, and larceny. Doing this for clearance rates helps us identify agencies that follow similar trends as the national average trend, and those who substantially differ from it (e.g., have much better or worse clearance rate trends). The goal of this analysis is to classify agencies to understand the relationship between their investigative practices and these patterns.

A. Homicide Clearance Trajectories

Because homicides are a rare crime and because clearances are even rarer, the calculation of homicide clearance rates (total cleared/total homicides) across agencies per year can vary widely. The wide variance in homicide clearance rates per year contributes to a difficulty of trajectory analysis to converge on a solution.[5] In prior work with group-based trajectory modeling, one of the authors discovered that raising the maximum value could aid the maximum likelihood estimator in converging on a maximum.[6] Thus, this technique was used here. The research team set the maximum value of the highest value of homicide clearance rates at a ten-fold increase. For the full data set, the maximum clearance rate was 10, so the maximum value for the full sample modeling was changed to 100 instead of 10 and for the subsample of the 100 largest agencies the maximum value was set to 40 as the maximum clearance rate in that data was 4.

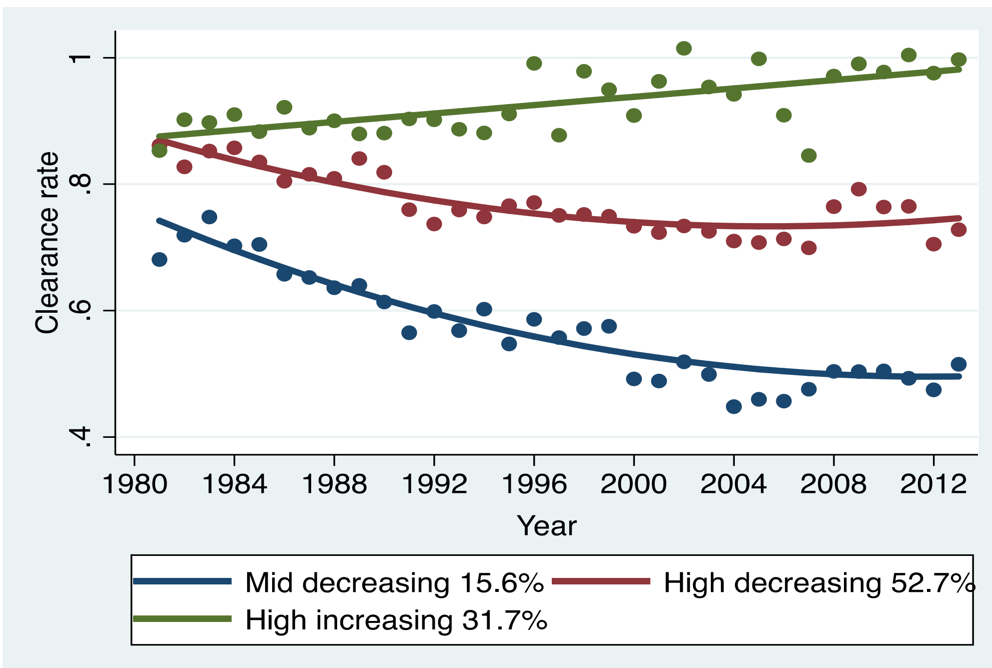
The censored normal model (CNORM) was selected as the best type of trajectory model for clearance rates given it is scale data which may contain clusters at the minimum or maximum of the data (Nagin, 2005). We set the parameters of each group (zero to third order), and added trajectories until the model either stopped improving (based on the BIC and AIC), began adding unsubstantial trajectory groups that simply split existing groups into fractal

[5] The method uses general quasi-Newton maximum likelihood estimation to identify parameters in the data that maximize the likelihood function.
[6] Discussion with experts in the method suggested that this approach was an acceptable alteration of the model.

representations, created trajectory groups containing fewer than 5% of the sample, or could no longer converge.

For our full model of 519 agencies[7] with 100 or more officers, we selected the 3-group model (BIC=-5397.82; AIC=-5374.43), as shown in Figure 3. The 4-group model produced one group with only 8 agencies, which falls under the criteria for at least 5% of cases in each trajectory group. The BIC for the 3-group model was an improvement over the 2-group model. Therefore, the 3-group model was selected as the optimal model. Under each figure, the proportion of agencies for each group are shown. The posterior probability for each of the four groups is 0.88 or above, which falls within Nagin's recommendation of greater than 0.7 for each group.

Figure 3. Trajectories of Homicide Clearance for Full Sample (n=519)

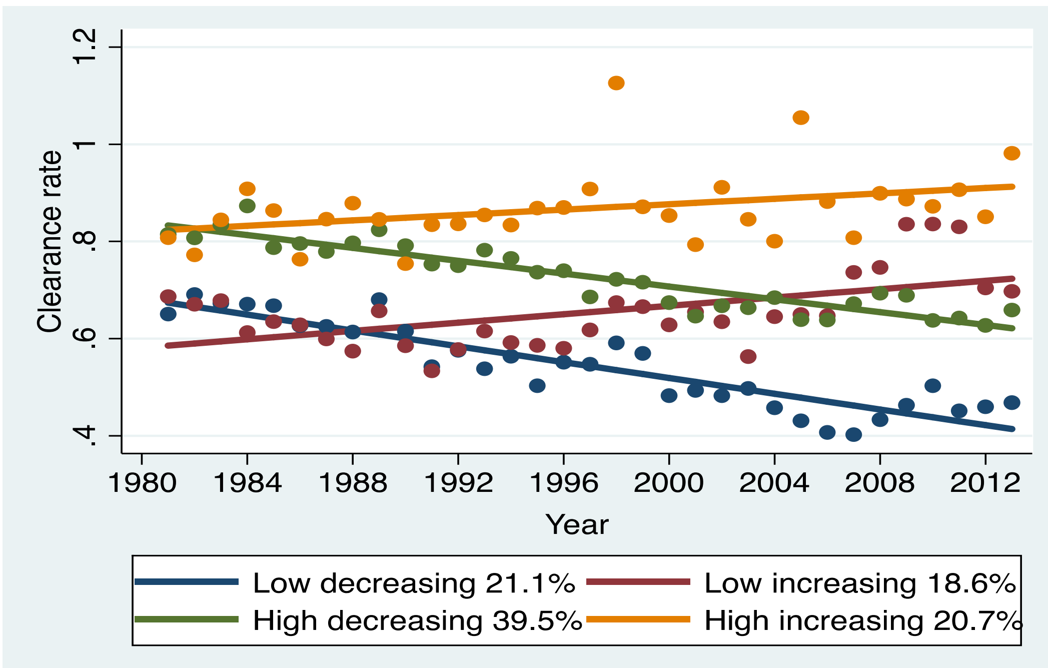


These results indicate that the downward nation-wide trend in homicide clearance is not the case when looking at specific agencies. Indeed, approximately 32% of agencies with 100 or more officers appear to have stable and even increasing homicide clearance rates over time. A large group of agencies (about 53%) also do not match the nationwide average trend in homicide clearances, beginning at higher rates in 1981, and dropping only slightly below the 80% range in 2013. Only 16% of our sample were consistently performing below the national average, declining in clearance over the study period.

[7] Recall, many agencies were excluded due to their missing data.

When examining only the subsample of the 100 largest agencies in the U.S., a 4-group trajectory solution fit the data best (BIC=393.70, AIC=408.83), consisting of four linear trajectories—two increasing and two decreasing as shown in Figure 4.[8] Both the BIC and AIC indicated that this model was an improvement over the three-group model, and a comparison using Jeffery's scale of evidence for Bayes factors suggested a similar conclusion. The posterior probability of correct classification was above 0.9 for each group. A five-group model did not converge on a solution.

Figure 4. Trajectories of Homicide Clearance for Largest Agencies Subsample (n=92)



Here, overall trajectory patterns mimic the larger sample, but with important differences. First, almost 40% of this subsample reflect the national trend; homicide clearance rates start off high and decline over time, from about 80% in 1981 to 60% in 2013. However, while only a small group of agencies in the full sample (recall, 15.6%) were consistently performing under the national average of homicide clearance rates over time, this group represents a larger proportion of this subsample (21%). This may indicate that the largest agencies (which likely also suffer from the greatest proportion of the nation's homicides) tend to fall more likely within a lower-performing group. As with the full sample, some agencies

[8] We did not purposefully try to fit the same number of trajectory solutions for our full sample and the subsample of the largest agencies. Rather, we conducted each analysis separately, with the objective of determining which sample would be most useful to carry out our further analyses in Phases II and III of this project.

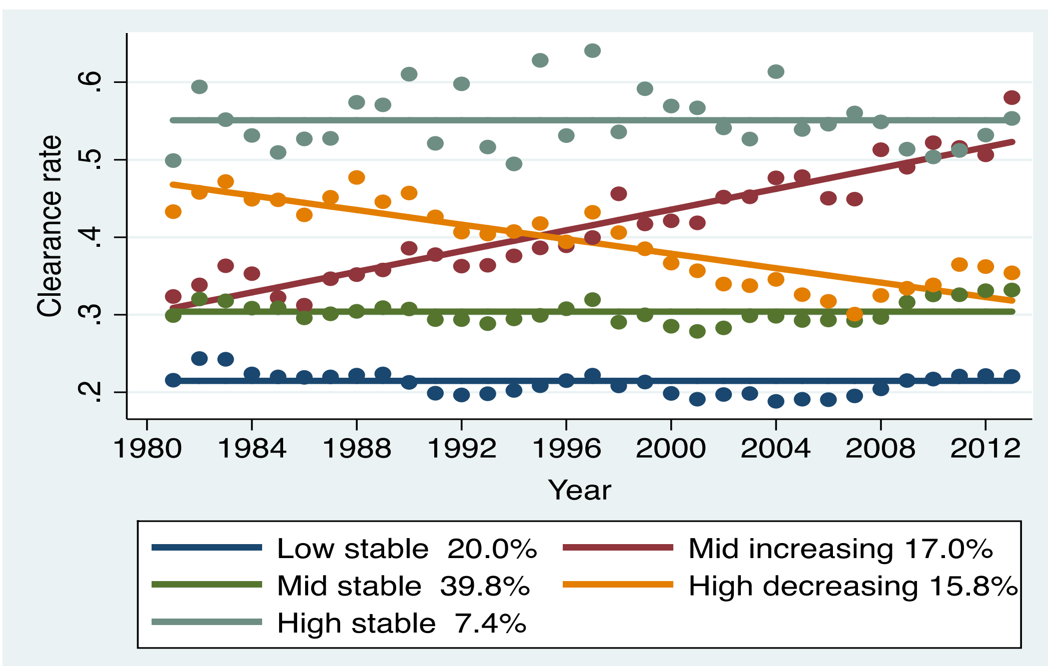
seem to be clearing homicide cases better than the national average (21%), showing improvement over time. And, there appears to be a group (around 19% of agencies) who performed below the national average in 1980 but seem to be improving over time with regard to homicide clearance. This group was not apparent in the larger sample.

Our analysis of homicide trends indicates that there is substantial variation in homicide clearance rate trends in U.S. agencies that were masked by the nationwide trend of homicide clearance as found by Cronin et al. (2007) and as shown in Figure 1. Similarly, as will be shown for robbery, aggravated assault, burglary, vehicle theft and larceny, the national trends of crime clearances can be deceiving when examining specific agencies using trajectory analysis.

B. Robbery Clearance Trajectories

The final trajectory solution selected for the full agency sample for robbery (n=729) was the 5-group solution (see Figure 5), as it had the highest BIC (11523.86) and AIC (11551.41) and added a significantly new trajectory group compared to the 4-group solution. The posterior probability of group membership was above 0.89 for each trajectory group.

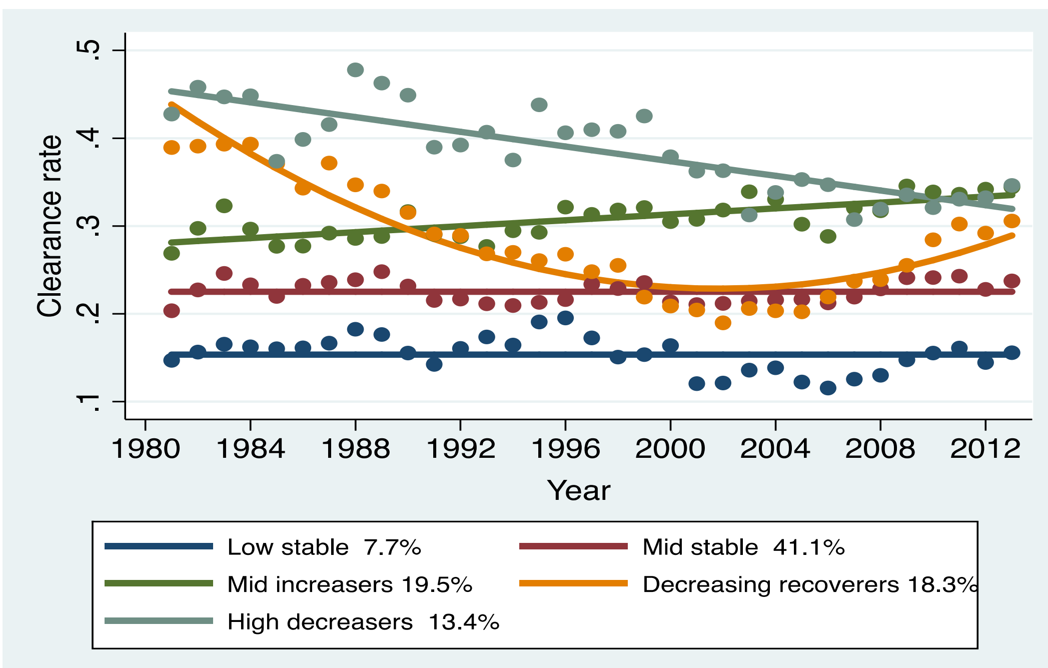
Figure 5. Trajectories of Robbery Clearance for Full Sample (n=729)



Recall in Figure 1 the average trend of robbery clearance for all agencies with 100 or more officers is stable, fluctuating between 32-38%. However, our trajectory analysis reveals agency-level variations. For example, although a significant proportion of agencies seem to follow this stable, low-clearance rate trend (about 40%), there appears to be at least 17% of agencies who have significantly improved their clearance of robberies, and another 7% of agencies who consistently perform much better than the national average. Further, about 20% of agencies consistently perform lower than the national average, with clearance rates of about 0.20, and another 16% of agencies who initially began at higher clearance rates in the early 1980s than the national average, but declined to the national average over the 32 year period of analysis.

When examining only the largest 100 agencies, a five-group solution also emerged (see Figure 6) based on the BIC (3422.44) and AIC (3440.0), and also because of the unique trajectory group introduced in the five group model, compared to the four. The six-group model, despite being favored by the information criteria, created a group that simply split the high decreasing group into two high decreasing groups, with one representing less than five police agencies.

Figure 6. Trajectories of Robbery Clearance for Largest Agencies Subsample (n=92)

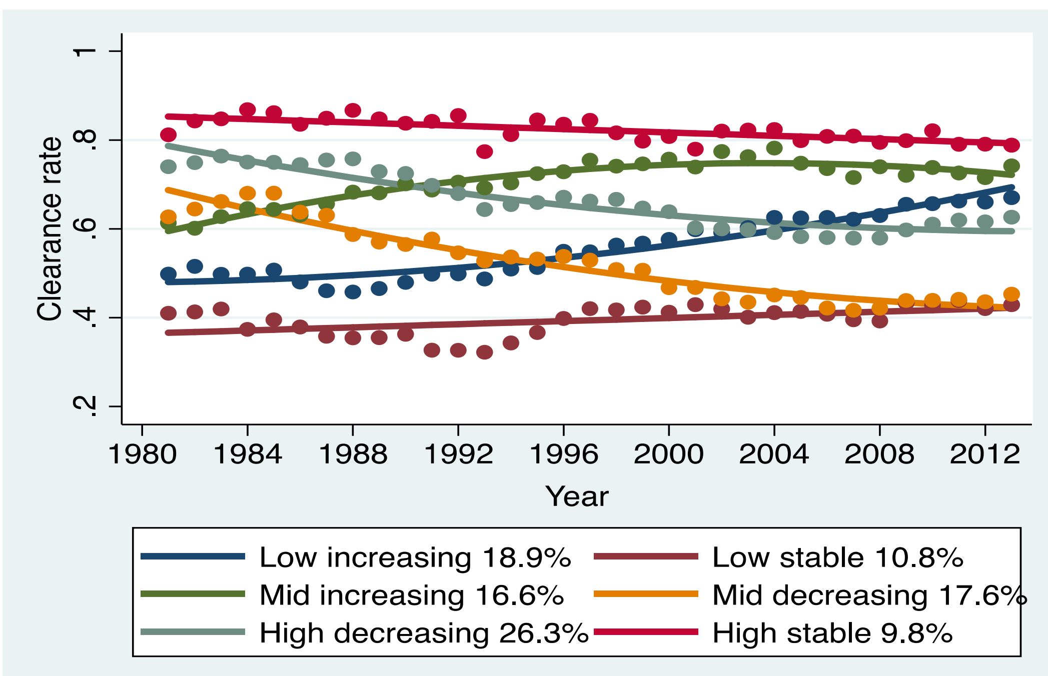


Interestingly, when analyzing the largest agencies, almost half seem to be performing under the national average in robbery clearance. This could be the case because these agencies are likely also agencies in which the prevalence of robbery is relatively high. Another 20% seem to be performing similarly to the overall trend with a slight increase in robbery clearances. Like the full sample, there are also agencies who start better than the national average in 1980 but have declining robbery clearances over time. And finally, there is a group that while on a sharp decline between 1980 and 2002, seems to be improving or "recovering" with regard to their robbery clearance rates.

C. Aggravated Assault Clearance Trajectories

The clearance rates of aggravated (or more serious) assaults tend to be higher, on average than other crimes, often because the suspect is known. When looking at the total aggravated assaults cleared in the U.S., clearance rates tend to hover around 60%. The trajectory analysis, however, reveals a very different finding. Here, the model selected was a 6-group solution (BIC=9216.51; AIC=9266.14) as shown in Figure 7. The posterior probabilities for each group are all above 0.91. Although a 7-group model did produce a lower BIC and AIC, it split the second and third trajectories into similar trajectories. The 6-group trajectory added a new group not present in the 5-group solution.

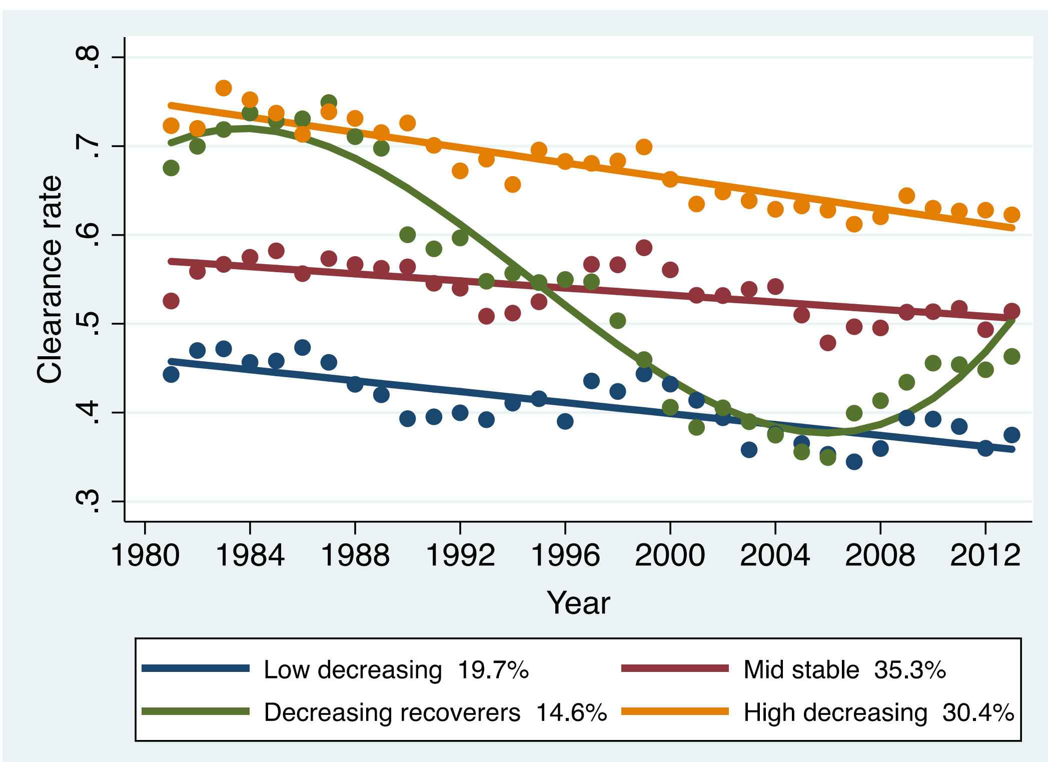
Figure 7. Trajectories of Aggravated Assault Clearance for Full Sample (n=673)



Here, 17% of our sample do follow (and actually exceed) the national trend, with clearances starting at 60% and increasing to over 70%. However, 11% of agencies perform significantly lower than the national average over time, and another 18% seem to be declining in their ability to clear aggravated assault cases. Interestingly, 19% of agencies begin with very low clearance rates in 1980, but then shoot up to the national average in 2013. Another 26% of agencies begin above the national average at over 80% but decrease to near the national average of 60%. Finally, about 10% of agencies have an extremely high clearance rate around 85%, which decreases slightly over time. Many questions arise here, including the influence of the reporting of domestic violence on these trends and why that change didn't seem to uniformly affect all agencies (for example, we might expect agencies to show continual improvement over time since the 1980s).

We also see some significant variation in aggravated assault clearance rates in the largest 100 agencies (Figure 8). We found that although a 5-group model showed the greatest improvement according to the BIC and AIC, it simply broke one group, the high decreasing trajectory, into two high decreasing trajectories. Since the BIC has a tendency to favor the creation of more groups when fewer appear to fit the data more appropriately, and since this new group did not add substantially to the explanatory picture, we decided to select the 4-group model as our optimal solution (BIC=2165.97; AIC=2183.15). The posterior probabilities were all above 0.95, meaning there is less than a 5% chance for each trajectory group that an agency was incorrectly classified to its "real" group.

Figure 8. Trajectories of Aggravated Assault Clearance for Largest Agencies Subsample (n=86)

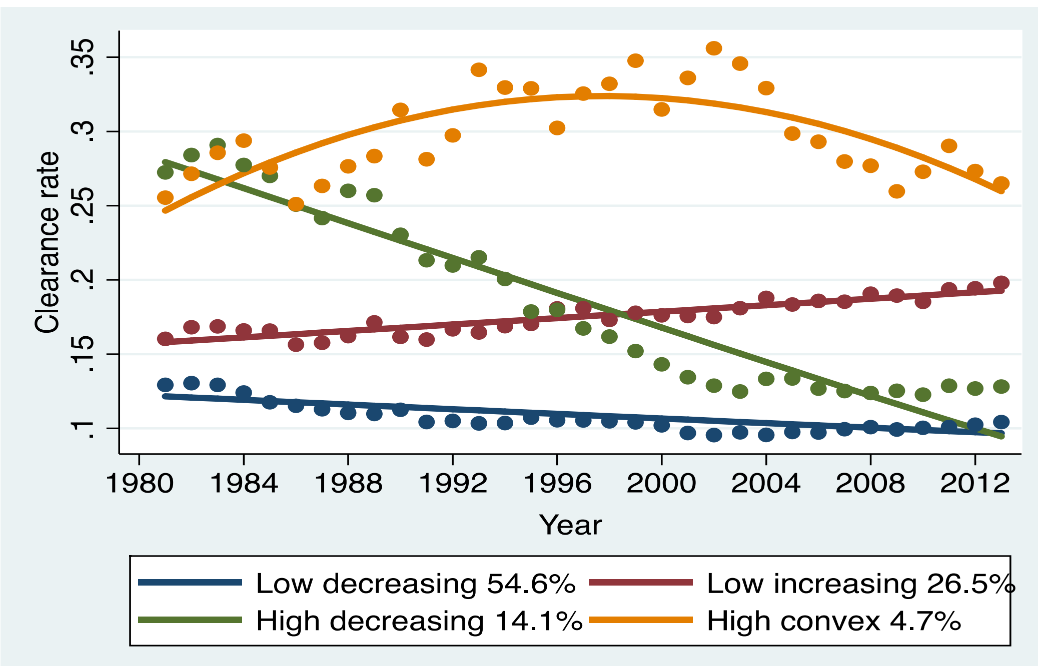


Many agencies, except for the 15% we label as "decreasing recoverers" seem to be declining in their ability to clear aggravated assault cases, although about a third of agencies appear to be at or above the national averages.

D. Burglary Clearance Trajectories

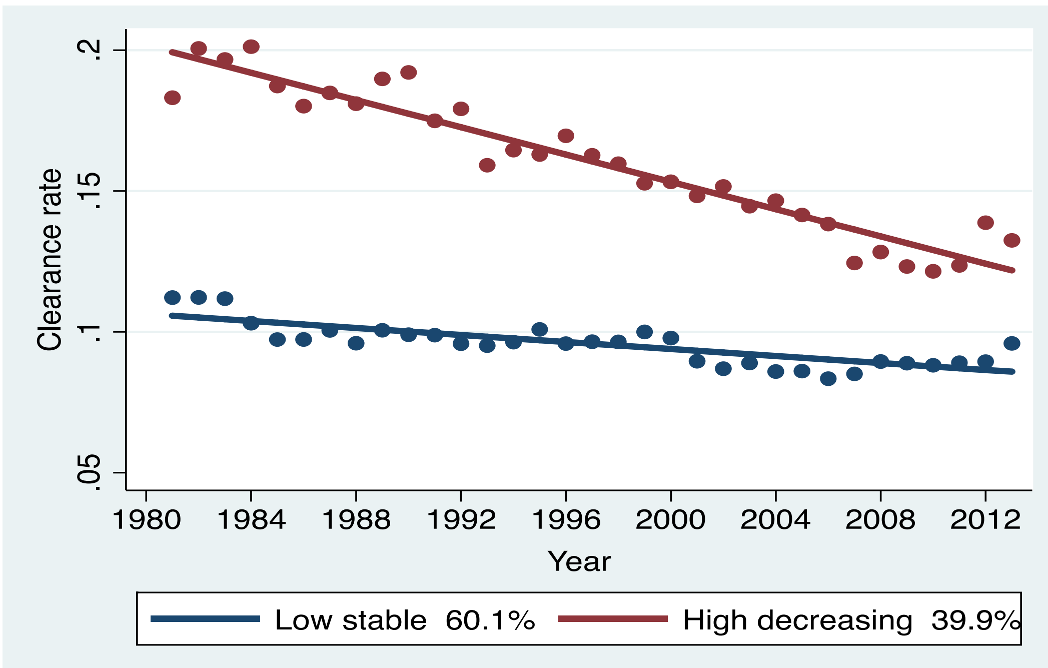
On average, burglary has traditionally suffered from a very low clearance rate for the last three decades in the U.S., hovering (if not slightly declining) around 14%. However, burglary is a major concern in many communities and police agencies. In our analysis, we find much less variation in the clearance of burglary across either our full sample of all agencies with 100 or more officers, or in our smaller subsample of the 100 largest U.S. agencies. For our full sample, we settled on a 4-group solution (BIC=28576.60; AIC=28606.69; posterior probability for each group >0.94). The solution is shown in Figure 9. The 5-group solution added one group that was under our 5% of cases threshold. Over half of our sample (nearly 55%) have a low, stable clearance rate that falls slightly below the national trend. However, a quarter of our sample (26%) begins with a low clearance rate and improves over time to nearly 20% clearance. 14% of agencies begin at a higher clearance rate of 28% but then drops to below the national average. Almost 5% of agencies begin at a higher clearance of 25%, improving in the late 1990s, but then dropping back to around 25%, which is still above the national average.

Figure 9. Trajectories of Burglary Clearance for Full Sample (n=757)



The model selected for the largest agency subsample revealed a two-group solution to be the best fit (BIC=4836.93; AIC=4844.49; posterior probability for each group >0.98) as shown in Figure 10. Again, while more groups can always be created, substantively new or distinct trajectories did not seem to appear. As with the full sample, most agencies seem to hover below the national average, while about 40% of the large agencies seem to have declining burglary clearance rates since the 1980s.

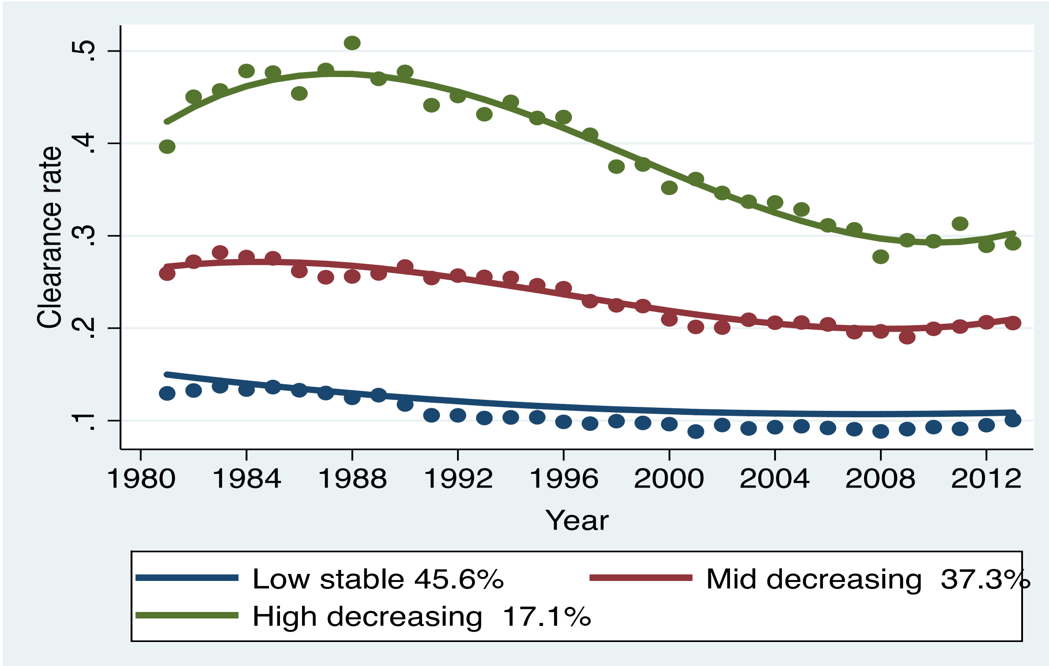
Figure 10. Trajectories of Burglary Clearance for Largest Agencies Subsample (n=92)



E. Vehicle Theft Clearance Trajectories

In general, vehicle theft has been on the decline, with the advent of better security technology for cars and changes in practices (e.g., not leaving keys in an unlocked and running car). Further, many vehicles are recovered (although agencies do not count recoveries as clearing a crime of vehicle theft by arrest or exceptional means). For our full sample of agencies with over 100 officers, a 3-group trajectory solution emerged (BIC=15948.74; AIC=15981.08; posterior probabilities for all groups >0.96) as shown in Figure 11.

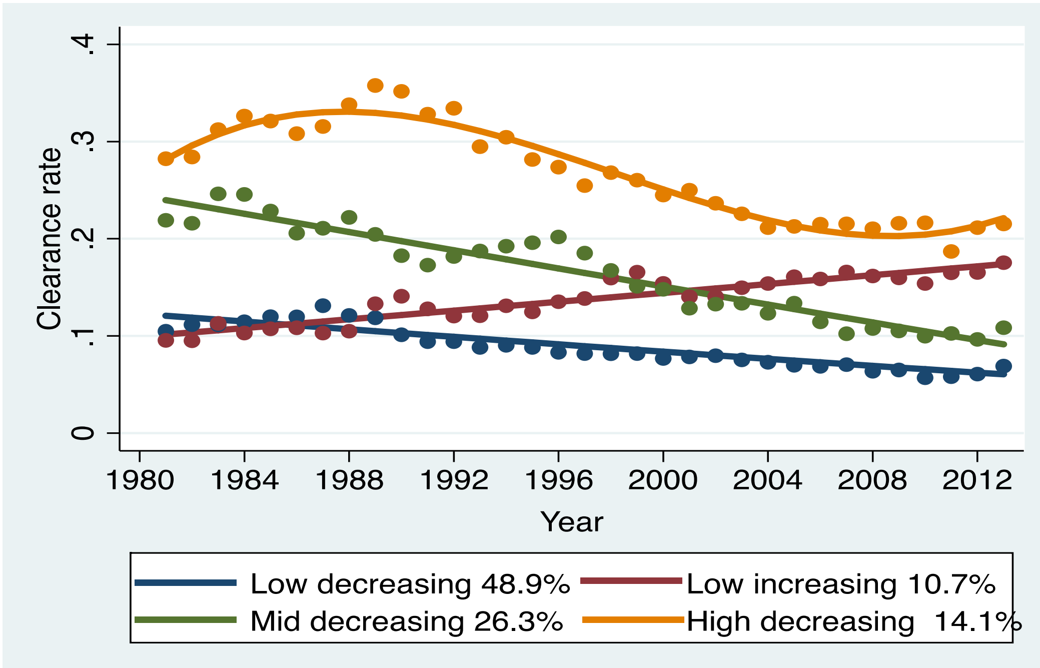
Figure 11. Trajectories of Vehicle theft Clearance for Full Sample (n=749)



Here, the largest proportion of agencies has a low and stable clearance rate of around 11%. Another group (37%) is very similar to the national trend, slightly decreasing but hovering around .25 clearance rate. The third group is the high decreasers, with 17.1% of the agencies starting at an above average clearance rate in the 1980s, dropping to a still above-average clearance rate in 2013.

Similar and different trends are found when examining the subsample of largest agencies (Figure 12). Here, we settled on a four-group model, as the addition of more trajectories after this point simply splits existing trajectories into smaller representations of the larger ones, retelling the same story albeit in a less parsimonious way. The posterior probabilities for the four-group model are all above .97, the BIC = 4134.28 and the AIC = 4151.94.

Figure 12. Trajectories of Vehicle Theft Clearance for Largest Agencies Subsample (n=92)

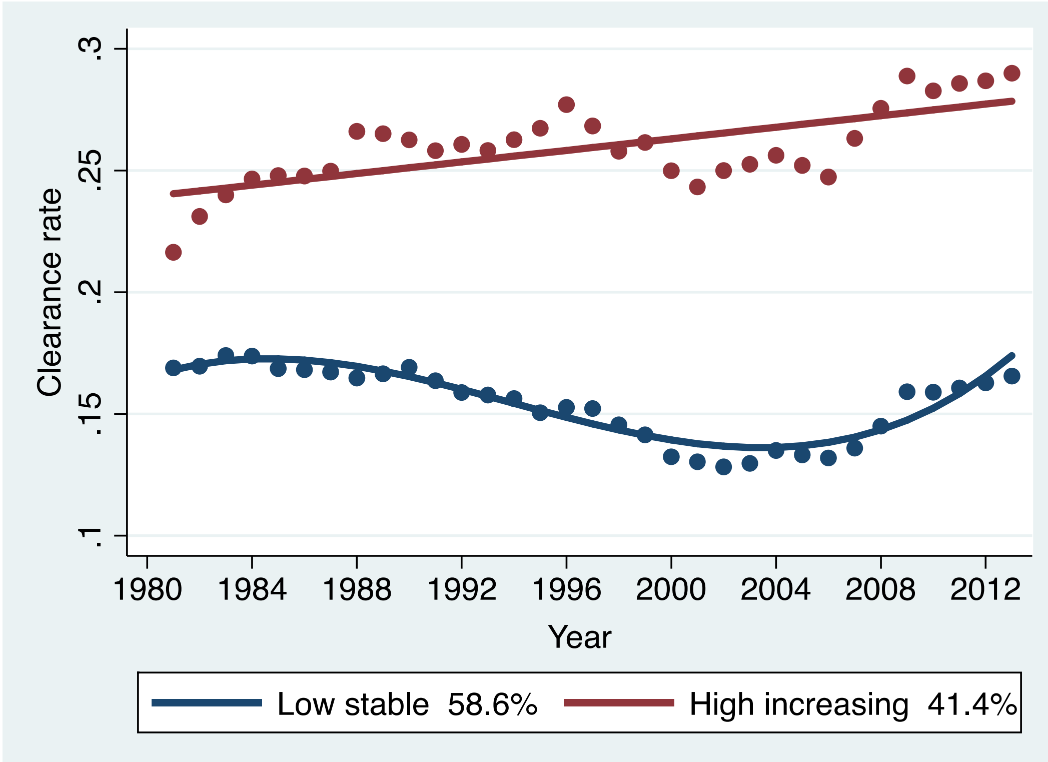


Like the full sample, almost half of the largest agencies have a low and also declining clearance rate for vehicle theft. Another 26% are declining towards the lowest group over time. However, in the largest agency subsample, a group of about 11% of agencies seem to be modestly improving in their vehicle theft clearance, from being below the national average to returning close to that average in 2013. And, another 14% of agencies perform better than their counterparts.

F. Larceny Clearance Trajectories

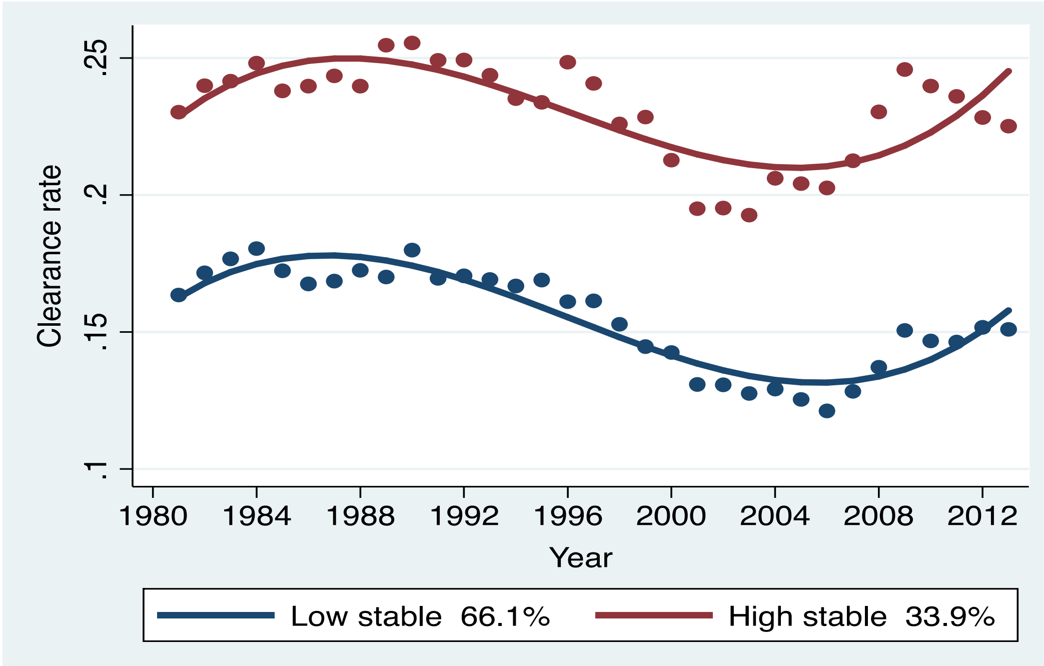
Finally, we examined larceny clearance trajectories. As with vehicle theft, national average trends for larceny clearance have hovered around 20%. For the full sample, we determined that the optimal solution was a 2-group solution (BIC=25840.77; AIC=25859.28; posterior probabilities at 0.98 for each group). The 2-group model, shown in Figure 13, was selected because the additional groups simply split trajectories in a non-meaningful way. This solution indicates that about 59% of agencies perform under the national trend while 41% of agencies perform above it (with some improvement over time).

Figure 13. Trajectories of Larceny Clearance for Full Sample (n=729)



Similarly, we find a two group solution when analyzing just the subsample of larger agencies (Figure 14). After the simple, two-group model, trajectories continued to split these trends into fractal representations though only a few clearance percentages off from the original. For this reason, the two-group model was selected as the best representation of the latent trajectories in the data (BIC=4524.91; AIC=4537.46; posterior probabilities >0.98). This two-group model included a low stable group comprised of 66% of the agencies and a high stable group representing 34% of the sample. Although these groups are labeled as stable because they start and end at similar places, one can see from the graph that both groups display a cubic pattern of growth by increasing, decreasing, and then increasing again.

Figure 14. Trajectories of Larceny Clearance for Largest Agencies Subsample (n=91)



G. Using Dual Trajectory Analysis to Explore the Relationship between Clearance Rate Trajectories and Crime Rate Trajectories

This rest of this project is devoted to understanding what might explain variations in clearance rate trends at the agency level over time by examining agency-level characteristics, investigative practices and policies within particular trajectories. We focus on our large-agency sub-sample in all future phases to limit the sample of agencies we will need to select from to survey and conduct case studies. Limiting ourselves to the top 100 agencies in the U.S. also allows us to control for factors of agency size and to focus on those agencies with likely the highest crime rates.

However, one possible explanation of our clearance rate trajectory solutions that we explore in this phase is whether clearance rate trajectories are related to crime rate trajectories over time. For example, if clearance rates impact crime rates, we might expect agencies that perform well in terms of clearance rates might also have low crime rates. As Nagin (1998, 2013) has reviewed, such analysis is difficult in coming to causal conclusions. For example, high clearance rates may be the result of low crime rates, reflecting the ability for agencies to devote more resources to solving less crimes.

While the use of trajectory analysis does not resolve these issues, we explored the relationship between agency trajectory membership and their crime rates over time to gain a sense of the crime-trend characteristics of these agencies. To do this, we carried out dual trajectory analysis on our already created trajectories of crime clearance for the largest agency subsample against newly created trajectories of crime rates for each of our six crime types. [9] This requires conducting trajectory analysis on crime rates over our time period (1981 – 2013) using the same approach as discussed above and then examining the probabilities of agencies who are members of particular trajectories of clearance rates are also members of specific crime rate trajectories (or vice versa).[10]

This dual trajectory analysis indicated that on average, across our crime types, cities with the lowest crime rates tend to have higher crime clearances over time, whereas cities with relatively higher crime rates tend to fall in lower crime clearance trajectories. We note this relationship is only an association, not a causal statement. There are many factors which influence crime rates, which may or may not include how well detectives clear particular types of crimes. However, it is important to note that previous cross-temporal correlation approaches between crime rates and clearance (or arrest rates) do not take into account that there may be latent groups within the distributions of clearance and crime rates that may better explain this relationship. A trajectory approach provides an innovative exploratory way of approaching this question.

[9] The results of the dual trajectory analysis for the full sample of agencies with 100 or more officers will be presented in Heather Vovak's doctoral dissertation (forthcoming).

[10] This results of the dual trajectory analysis are as lengthy as the analysis presented in this report, and are omitted here due to our focus on the trajectories of crime clearance themselves. However, these results will be presented in academic articles.

Next Steps

When examining overall year-to-year clearance rates at the aggregate, nationwide level for serious crimes, a story of stable clearance rates emerges over the period of study (1981 – 2013). However, we hypothesized that this overall trend might mask variations in long-term trends of clearance rates across individual agencies. In our analysis, we found substantial variations in clearance rate trajectories, especially for homicide, robbery, aggravated assault and vehicle theft. For burglary and larceny, while some agencies did perform slightly above and below the overall trend, these trajectories tended to follow the average nationwide trend more closely, and also resulted in much fewer trajectory groupings. In other words, it appears that some law enforcement agencies are much better (or worse) at clearing particular types of crime compared to their counterparts.

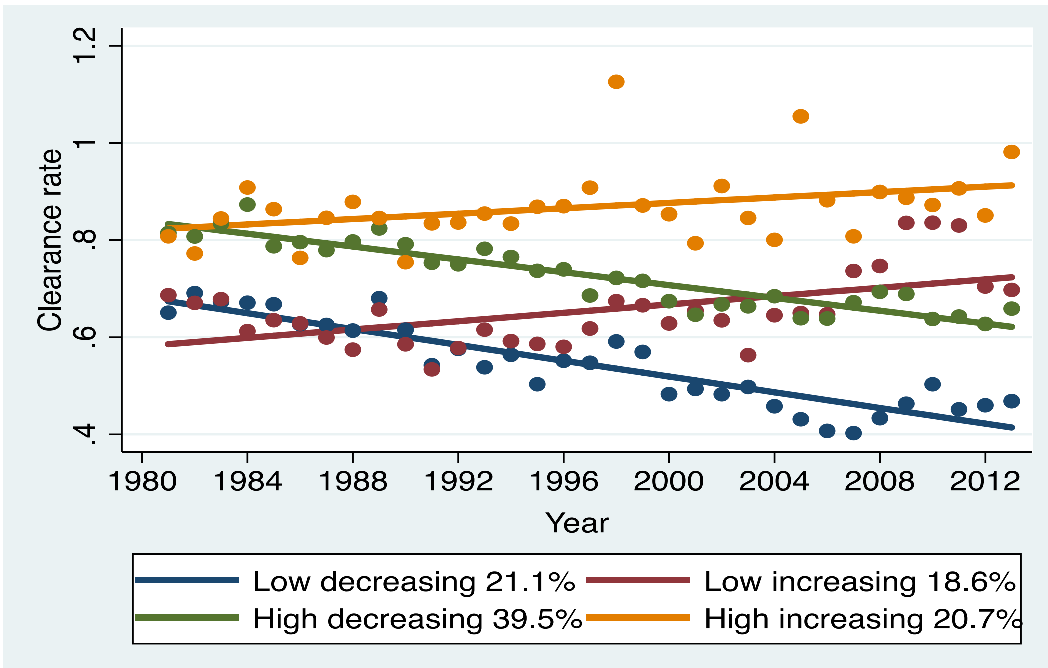
These variations persist, even when examining the largest 100 agencies in the U.S. (excluding state police agencies). These agencies account for a disproportionate amount of the nation's crime (approximately 41% of all homicide, robberies and aggravated assaults in the U.S. and about 29% of all burglaries, vehicle theft and larcenies). Yet, they continue to vary with regard to their long-term clearance rates for various crime types. The important question is "why"? While there is some indication that agencies with lower crime rates tend to have higher clearance rates, the results of our dual trajectory analysis only scratches the surface of understanding why agencies vary in their clearance rate patterns.

Selecting Agencies for the Next Phases

The rest of this project is devoted to understanding why some agencies perform better than others, and more specifically for our subsample of the largest 100 agencies. Sharpening our focus on this subsample will allow us to home in on what might explain variations in trajectories across our various crime types. One challenge is that we have six crime types for each of these agencies, with varying clearance trajectories. Some agencies may divide their investigative units neatly into these crime types, but some agencies do not. Finding a way to characterize an agency's ability to clear serious crimes more generally would be helpful in identifying agencies for further study. To characterize our top 100 agencies in terms of their overall clearance rate trajectories across all crime types, we carried out the following analysis, in consultation with trajectory modeling experts.

First, every trajectory for each of our crime types were given a numerical identifier, according to (generally) their lowest to highest clearance rate trajectory. For example, our trajectory solution shown in Figure 4 is shown again below. The "low decreasing" trajectory was labeled as "1", the low increasing as "2", the high decreasing as "3" and the high increasing as "4". This coding was done for all trajectory solutions for the largest agencies subsample.

Figure 4. Trajectories of Homicide Clearance for Largest Agencies Subsample (n=92)



We also used the probability given by the trajectory analysis for each agency being assigned to a specific trajectory. So, for example, Agency "A" might have a 85% probability of being assigned to the low decreasing group in Figure 4. This information allowed us to do two analyses to identify agencies for our next research phases. First, given that we had the trajectory grouping and the probability of any given agency falling into that trajectory grouping, then for each agency and for each crime type we now have the following information as shown in Figure 15. This includes the specific agency name, the particular trajectory for each crime that it fell into (roughly classified from low to high clearance rates), and the probability of assignment of that agency into that trajectory.

Figure 15. Characterizing Agencies across Clearance Trajectories

Agency	Homicide	Robbery	Burglary	Autotheft	Larceny	Assault	Tot/Wtot
Agency A	1 (1.0)	2 (.87)	1 (1.0)	3 (1.0)	1 (1.0)	1 (1.0)	9 /8.74
Agency B	2 (.97)	4 (1.0)	1 (1.0)	1 (.99)	2 (.99)	4 (1.0)	14/13.91
Agency C	3 (.99)	5 (1.0)	2 (1.0)	3 (1.0)	2 (1.0)	4 (1.0)	19/18.9
Agency D	4 (.99)	3 (1.0)	2 (1.0)	1 (1.0)	2 (1.0)	4 (1.0)	16/15.96
Agency E	1 (.98)	2 (1.0)	1 (1.0)	1 (1.0)	1 (1.0)	4 (1.0)	10/9.98

The "Tot" represents the total sum of the trajectory classification. So for Agency A,

"Tot"= 1 + 2 + 1 + 3 + 1 + 1 = 9

The "Wtot" represents the sum of the trajectory classification weighted by the probability of assignment into that trajectory. So, for Agency A,

"Wtot" = (1*1.0) + (2*.87) + (1*1.0) + (3*1.0) + (1*1.0) + (1*1.0) = 8.74

Using Tot/Wtot allows us to see overall how well an agency was classified across multiple crime types, with Tot/Wtot = 1 considered an optimal classification. Tot/Wtot also allows us to determine, based on its magnitude, whether an agency is a higher or lower performer with regard to crime clearance. Once high and low performers are identified, we will confirm our findings with the actual crime clearance data for those agencies. Using this approach will be used in the selection of agencies in our next phases.

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