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Nemschoff, Danielle

University of Chicago

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An Evaluation of Crisis Intervention Team Training

Danielle Nemschoff*

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Abstract

Police officers in the United States are often the first responders to mental health crises, despite growing concerns about whether traditional policing is well-suited to these encounters. One response has been crisis-intervention team (CIT) training for police. Unlike alternatives such as unarmed responders or co-responder models, CIT seeks to improve outcomes by training officers to de-escalate mental health crises themselves. This paper provides causal evidence on whether CIT training reduces police use of force and arrests during mental health incidents. I construct a comprehensive administrative dataset linking calls for service, police reports, use-of-force records, officer demographics, and detailed training records from the New Orleans Police Department from 2017 through 2023. To estimate the causal effect of CIT training, I use a difference-in-differences framework that exploits variation in the timing of training across officers. Specifically, I compare changes in propensity to use force and make an arrest for officers before and after they receive training to those of officers who are not-yet-trained but will be trained in the future. I find no evidence that CIT training reduces officers' use of force or likelihood of making an arrest in mental health incidents. I also find no spillover effects on officer behavior in other types of calls. Importantly, officers who select into training are officers who are already less likely to use force even prior to training, indicating strong positive selection. Taken together, these results suggest that voluntary training programs, as currently implemented, may not meaningfully change officer behavior and instead primarily attract officers who are already less prone to use force.

1 Introduction

Criminal justice systems have become a primary site for managing mental illness: Los Angeles County Jail, Cook County Jail, and Rikers Island Jail Complex each house more individuals with mental illness than any remaining psychiatric hospital in the United States Research and Affairs (2016). Because police are often the first responders to individuals experiencing mental health crises, they play a central role in determining how these cases enter and move through the system. It is estimated that 21 to 38 percent of 911 calls nationally are related to mental health Research and Affairs (2016). Additionally, individuals experiencing a mental health crisis are disproportionately more likely to be killed during an interaction with police, and between 2015 and 2022, 22 percent of those shot and killed by police were reported to be in a mental health crisis (Julie Tate 2022).

In response to the growing demand for police involvement in mental health crises, departments have adopted a range of response models. These include traditional police response with specialized training, co-responder models, and non-police response. Co-responder models pair police officers with unarmed mental health professionals, social workers, or trained community volunteers, while non-police responses rely entirely on these non-law enforcement personnel. This project examines one of the most popular police trainings for a police-response model called crisis-intervention team (CIT) training. The goal of CIT training is to teach police officers how to de-escalate mental health crises and divert civilians in mental health crisis from the criminal justice system to health care and social services. This paper does not take a normative stance on when or if use of force is necessary, justified or excessive, but rather evaluates the program on the goal set

*PhD Candidate, University of Chicago Harris School of Public Policy. Email: dinemschoff@uchicago.edu. I would like to thank Dan Black, Manasi Desphande, Evan Rose, Dmitri Koustas, Bocar Ba, Derek Neal and participants at the Harris PhD seminar for their helpful comments.

forth of de-escalation from arrest and force. To my knowledge, this is the first paper to empirically study the causal effects of CIT training on police use of force and propensity to arrest.

To study this question, I construct a comprehensive dataset of emergency police response in New Orleans by merging multiple administrative sources, including calls for service, police reports, use-of-force reports, officer demographic records, and officer training schedules. The resulting data cover all police calls for service in New Orleans from 2017 through June 2023 and allow me to follow an incident from the 911 call to its conclusion. This allow me to examine how CIT training affects officers' use of force and arrest decisions. In my preferred specification, I implement a difference-in-differences design that compares officers before and after training, using future trainees as the control group in each month. I find no discernible effect of CIT training on either propensity to use force or make an arrest.

I also examine whether training has spillover effects on officer behavior outside of mental health incidents, including drug-related incidents and violent crime. While CIT is designed to improve responses to mental health crises, the de-escalation techniques it teaches may generalize to other types of encounters. If officers apply these skills more broadly, training could affect use of force and arrest behavior even in incidents that are not classified as mental health–related. I again find no discernible effect on either propensity to use force or make an arrest.

This paper contributes to a growing literature on emergency responses to mental health crises. Dee and Pyne (2022), Davis et al. (2025), and Ba et al. (2025) study unarmed community response programs across a range of settings and consistently find reductions in arrests and crime, as well as increased access to services and responses to calls that might otherwise go unanswered. In contrast, Dee and Pyne (2025) examine co-responder programs, in which mental health professionals respond alongside police, and find large reductions in involuntary psychiatric detentions with no effect on arrests or crime. This paper contributes to this literature by examining how a police responser model with specialized training affects policing outcomes, rather than alternative responders.

This paper also contributes to a growing economics literature on police training. McLean et al. (2020) studies the impact of social interaction training for police and similarly find it has no impact on officer use of force. Owens et al. (2018) and Dube, Shah, and MacArthur (2022) both develop, implement and evaluate training programs and find that officers who receive training were less likely to use force and less likely to make discretionary arrests. Rather than evaluating a specific program, Adger, Ross, and Sloan (2022) attempt to identify how the behavior of a field training officer impacts their trainees and find that recruits who had field training officers with higher use of force also demonstrate a higher use of force, shedding light on a possible avenue for effective change. This paper contributes to this literature by estimating the causal effects of mental health response training on individual policing outcomes.

The paper proceeds as follows: Section 2 provides a background on police response to 911 calls and crisis-intervention team training in New Orleans, Section 3 discusses the data and presents summary statistics. Section 4 details the empirical strategy, Section 5 presents results and discussion, and Section 6 concludes.

2 Background

2.1 911 calls and Police Response in New Orleans

Police officers interact with the public either in response to 911 calls or through self-initiated stops. Due to endogeneity concerns of self-reported stops, I focus solely on interactions that originate from 911 calls.

Calls for service are received by the New Orleans Police Department's (NOPD) Communications Division. Basic metadata, including the time and location of the call, are recorded in the Computer-Aided Dispatch (CAD) system. The call-taker assigns an initial incident classification and priority level, determines whether a response is required, and dispatches the appropriate service.If a police response is deemed necessary, officers are dispatched in one-man units based on call priority and proximity to the incident.[1] Dispatch and arrival times are recorded in CAD.

After responding to the incident, officers assign a final disposition in the CAD system. Incidents may be classified as "null" or "void" if the incident was falsely reported, or as "gone on arrival" if the relevant

[1] According to correspondence with NOPD Public Information, the default is to dispatch one officer per call. However, dispatchers may assign multiple units depending on the priority and description of the call and officer availability. Officers closest to the incident are dispatched, and additional units may respond if backup is requested.

parties are no longer present. If involved individuals are present, the disposition is typically either "necessary action taken (NAT)" or "report to follow (RTF)". An incident is classified as NAT if no arrest is made, no report is filed, and no substantial action is taken at the scene. In these cases, I do not observe additional information about the incident or responding officers. If the disposition is RTF, officers file a formal report documenting the details of the incident, including the number and characteristics of offenders and victims. I observe reports for approximately 20–30 percent of calls each year.[2] These reports are based on officer observations, as well as victim and witness statements.

NOPD policy requires that any use of force beyond non-resisted handcuffing be documented in a separate use-of-force report. These reports are completed by a supervising officer and include information on the officers and subjects involved, the type and level of force used, injury status, and relevant contextual factors.[3] I also observe these use-of-force reports.

2.2 Crisis-Intervention Team Training

One of the most common mental health crisis de-escalation trainings given to police officers is called crisis-intervention team (CIT) training. The version of CIT used in most police departments today is called the Memphis Model, which was developed by the National Alliance on Mental Illness (NAMI) of Tennessee in 1988 (Memphis CIT Center 2022). NAMI estimated that as of 2008 there were over 400 CIT programs across the US and by 2019 there were over 2,700 programs (Mental Illness 2022). While there has been little academic study of CIT, there are plenty of anecdotal claims of success. On their website NAMI claims "...programs like CIT reduce arrests of people with mental illness while simultaneously increasing the likelihood that individuals will receive mental health services." They also make the specific claim that "in Memphis, for example, CIT resulted in an 80 percent reduction of injuries sustained by officers during mental health crisis calls."

The New Orleans Police Department established a CIT training program in 2015 as part of a federal consent decree established in 2013. As of June 2023, there had been 17 cohorts of officers to receive CIT training.[4] In total 365 officers received training between 2015 and 2022, representing approximately 30 percent of all patrol officers.[5]

In New Orleans, incidents classified as "emotional disturbed person", "mental patient", "suicide threat", "suicide attempt" or "suicide" are prioritized to receive a response from a CIT-trained officers. CIT-trained officers responded to about half of the calls with these classifications over the sample period. Protocol is for the dispatcher to locate the nearest CIT-trained officer when a mental health call comes in and dispatch them if they are available. If a CIT officer is not available, the closest officer is dispatched.

During the sample period, NOPD implemented several additional reforms under the federal consent decree. Most notably, the department revised its use-of-force policies, introducing stricter guidelines, expanded training, and improved data collection. These changes were motivated by findings of disproportionate and unnecessary use of force in the Department of Justice investigation.[6] NOPD also introduced a peer-intervention training program, EPIC, which trained officers to intervene when colleagues engaged in potentially inappropriate behavior. This program included instruction on bystander intervention and scenario-based exercises focused on de-escalation. These reforms were implemented department-wide rather than targeted to CIT-trained officers. As a result, they may affect overall levels of use of force but do not differentially affect CIT and non-CIT officers.

[2]Approximately 60 percent of RTF calls have an associated report, and a small number of calls with other dispositions also result in reports.

[3]One of the main findings of the Department of Justice investigation into the NOPD in 2011 was that officers use of force was "a clear pattern of unconstitutional uses of force" but that NOPD had not disciplined any officer in at least the past six years. The report also specifically notes the use of "significant force against mentally ill persons where it appeared that no use of force was justified". These findings motivated the requirements for better use of force training and reporting, and specific training for use of force in incidents of mental illness.

[4]There first class was in 2015, then there were three training cohorts in 2016, four in 2017, two in 2018, two in 2019, one in 2020, and one in 2021.

[5]From communication with NOPD, I learned that the majority of officers signed up voluntarily while some were selected for the program. There is no documentation available on which officers volunteered versus those who were selected.

[6]NOPD also issued body-worn cameras during this period, though data on their use are not available.

3 Data

The data for this project consist of all 911 calls for service in New Orleans between January 1, 2017 and June 30, 2023. For each call, I observe the incident date and time, dispatch time, responding officer identifiers, arrival time, incident classification, and final disposition. I then restrict the sample to calls with a disposition of "report to follow" or "necessary action taken" as these are the calls with a likely police-civilian interaction (this excludes calls labeled "gone on arrival", "unfounded", and "null"). This results in a sample of 100,000 to 200,000 calls per year.

I combine these records with multiple administrative data sources, including police reports, use-of-force reports, Crisis Intervention Team (CIT) records, and officer demographic data. A key feature of the data is that I can link arrests and use-of-force incidents back to the originating call for service. Stop-and-search data, traffic stops, and police reports are all conditional on officer-initiated contact. Because officers exercise discretion in whom they approach and how they respond, such data are subject to selection bias. In contrast, dispatch data allow me to observe all calls to which officers are assigned, regardless of whether an arrest is made, force is used, or a report is filed.

Call data. The call-level data include the dispatcher-assigned priority level, incident classification (e.g., assault, homicide, disturbance), date and time the call was received, dispatch time, block-level location, and the employee IDs of dispatched officers. Importantly, I observe only the officers initially dispatched to each call. I do not observe officers who arrive later as back-up or are subsequently assigned to the scene. Approximately 22 percent of calls between 2017 and 2023 are missing an officer identifier and I exclude these from the analysis.[7] Table 1 provides descriptive statistics of the sample of calls for service.

I define mental health calls as those classified by the dispatcher as "mental patient", "emotionally disturbed person", "suicide", "suicide threat", or "attempted suicide". Mental health calls account for 2–4 percent of calls for service each year. Table 2 presents descriptive statistics for the sample of mental health calls.

Police reports. Police reports contain the incident classification and priority level, date and time, and block-level location. They also include the race and gender of each offender and victim, when available, and identify the reporting officer. Reports are written by responding officers and reflect their account of the incident. All arrests are accompanied by a police report, and I use these records to measure arrest outcomes. Approximately 30-40 percent of calls for service result in a police report each year.

Use-of-force data. The use-of-force data include the date and shift of the incident (an eight-hour window), location by police district, and detailed information on each officer and subject involved, including demographics, type and level of force used, injury status, and whether the subject was hospitalized.[8] I link each use-of-force incident to its originating call for service using a crosswalk provided by the NOPD. Less than 1 percent of calls each year are recorded as resulting in force. It is important to note that force is determined by the perspective of the officers involved.

CIT data. The CIT data include (i) a list of incident numbers to which CIT-trained officers were dispatched and (ii) rosters of officers who completed CIT training, along with their training dates.[9] About one-third to one-half of all calls are responded to by a CIT-trained officer.

Officer demographics. Officer-level data include the name, race, gender, age, assigned district, hire date, and (if applicable) retirement date for all commissioned NOPD officers between 2017 and 2023.

[7] Over 90 percent of mental health calls include identifiers. And over 83 percent of calls with dispositions NAT and RTF have identifiers. Missingness skews toward unfounded and gone on arrival calls where there was likely no officer interactions.

[8] A full definition of use of force is provided in the appendix.

[9] Training began at the end of 2015, but dispatch data are only available beginning in 2017. As a result, I observe which officers were trained prior to 2017 but cannot identify the specific calls to which they were dispatched before that date.

3.1 Descriptive Statistics

I first demonstrate that officers listed as participating in CIT training were in fact removed from regular patrol duties during the training period. CIT training consists of 40 hours conducted over the course of one week, and Figure 1 shows that the number of calls officers respond to drops substantially during the week of training, consistent with removal from regular patrol and participation in training.

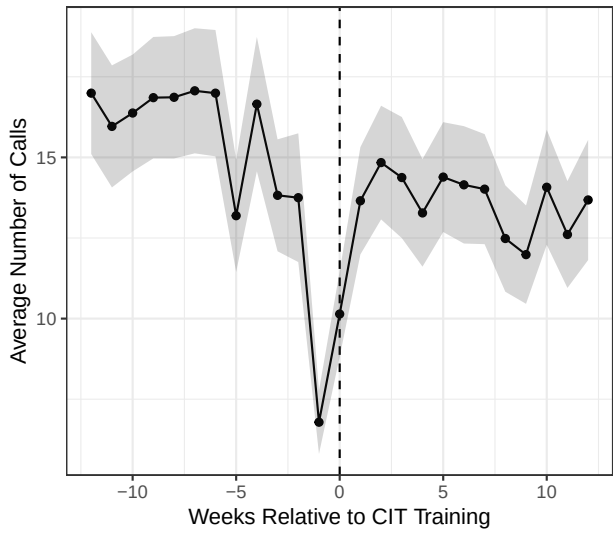

Figure 1: Officer Call Activity Before, During, and Post Training

Notes: This figure plots the number of calls a CIT-trained officer responds to each week in the 12 weeks prior to training, the week of training, and the 12 weeks after training. This figure demonstrates that officers responded to significantly fewer calls during their week of training, consistent with them actually participating in training.

Table 1 presents summary statistics on all calls for service from 2017 through mid-2023. There were 100,000 and 200,000 calls annually, with the vast majority of which involving non-violent incidents. Disturbance-related incidents constitute the most common incident type. Despite the large volume of calls, only about one third of all calls result in a police report and only 10–15 percent resulted in an arrest. Reported uses of force were rare, occurring in less than 1 percent of incidents each year.

Table 2) presents summary statistics for all mental health-related incidents from 2017 through mid-2023. CIT-trained officers responded to around half of all mental health calls for service each year. Mental health calls are more likely to result in use of force than they are in arrest. This low rate of arrest is likely due to the department wide mandate, accompanying the consent decree, instructing officers to bring those in mental health distress to a medical center rather than arresting them. However, mental health calls still have a disproportionately high-share of use of force incidents given their share of overall calls – 0.007 percent of mental health calls result in use of force, meaning mental health calls are seven times more likely to result in force than the average call. The top three call types to result in force in order are "other", "drugs" and "mental patient".[10] Furthermore, mental health calls with a CIT-trained officer dispatched are just as likely to result in use of force (about 1 percent) as incidents without a CIT-trained officer dispatched.

[10]See Appendix Table A4.

Table 1: Incident Descriptive Statistics

	2017	2018	2019	2020	2021	2022	2023*
N Incidents	196,442	190,865	153,143	119,704	127,867	110,340	56,500
Modal priority level	1	1	1	1	1	1	1
% police report	0.33	0.36	0.37	0.40	0.44	0.44	0.45
% property crime	0.07	0.08	0.10	0.11	0.12	0.14	0.17
% violent crime	0.02	0.02	0.02	0.03	0.03	0.03	0.04
% domestic	0.06	0.08	0.07	0.09	0.08	0.07	0.06
% welfare check	0.05	0.10	0.13	0.07	0.04	0.01	0.01
% disturbance	0.13	0.13	0.13	0.16	0.14	0.12	0.10
% mental health	0.02	0.03	0.03	0.03	0.04	0.04	0.03
% CIT dispatch	0.48	0.50	0.46	0.40	0.38	0.36	0.37
% arrest	0.09	0.09	0.11	0.11	0.14	0.15	0.16
% force used	0.002	0.002	0.002	0.002	0.002	0.003	0.003

Notes: *Only January 1, 2023 – June 30, 2023. The possible priority levels are 0–4. 0 indicates an administrative duty, 1 is lowest priority and 4 is highest priority. The two potential call dispositions are "report to follow" and "necessary action taken". Percent police report indicates the percent of calls where an official police report was written, as opposed to being resolved as "necessary action taken". The most common call classification is "complaint - other".

Table 2: Mental Health Incident Descriptive Statistics

	2017	2018	2019	2020	2021	2022	2023*
N Incidents	4,226	4,961	4,259	4,110	4,711	3,904	1,875*
% police report	0.11	0.12	0.12	0.14	0.17	0.15	0.12
Modal priority level	2	2	2	2	2	2	2
% emotionally disturbed person	0.94	0.91	0.90	0.88	0.86	0.71	0.17
% suicide	0.06	0.02	0.01	0.01	0.01	0.01	0.01
% suicide threat/attempt	0	0.07	0.09	0.11	0.13	0.27	0.82
% CIT response	0.53	0.57	0.51	0.43	0.43	0.4	0.36
% arrest	0.001	0.001	0.001	0.002	0.003	0.003	< 0.001
% force used	0.01	0.01	0.02	0.02	0.02	0.03	0.03

Notes: *Only January 1, 2023 – June 30, 2023. The possible priority levels are 0–4. 0 indicates an administrative duty, 1 is lowest priority and 4 is highest priority. The two potential call dispositions are "report to follow" and "necessary action taken". Percent police report indicates the percent of calls where an official police report was written, as opposed to being resolved as "necessary action taken". The classification "emotionally disturbed person" replaced "mental patient" in 2020, and refers to the same type of incident. Prior to 2018, suicide attempts and threats were classified as "suicide".

Table 3 presents descriptive statistics on the sample of patrol officers. There are eight police districts in New Orleans. The distribution of officer demographics is relatively steady over-time but does meaningfully differ between districts. Years of service and office age are balanced between districts but racial and gender composition are not. For instance, District 4 has a much higher share of Black and female officers compared to any other district. I include district fixed effects in all analysis to account for these differences. Average demographics of each district are presented below. I also check for demographic differences by shift. Ba et al. (2021) show that Black officers are assigned different shifts than white officers in Chicago. However, I see no systematic differences in the race or gender make-up within shifts. Table A4 in the Appendix shows officer demographics by shift.

CIT-trained officers are relatively uniformly distributed across districts and years (ranging from 5–12 percent of officers). Less experienced officers and female officers were much more likely to have received CIT training than other officers. This systematic difference in observables between trained and untrained officers motivates my use of only will-be-trained officers as counterfactuals for currently-trained officers, rather than additionally relying on untrained officers.

Table 3: Officer Demographics by District

District:	1	2	3	4	5	6	7	8
N patrol officers	78	81	81	75	81	75	84	100
Avg Age	39	41	42	42	41	40	40	41
Avg Years of Service	12	12	12	13	13	12	12	13
% Black	0.38	0.48	0.34	0.71	0.50	0.39	0.55	0.45
% white	0.42	0.43	0.54	0.22	0.31	0.49	0.25	0.42
% female	0.17	0.24	0.17	0.31	0.25	0.22	0.26	0.20

Note: Statistics are averages per month over January 2017–June 2023. The First District covers central residential neighborhoods, the Second District covers the Tulane-area, the Third District covers northern neighborhoods along Lake Pontchartrain, the Fourth District is located on the western side of the city, the Fifth District covers eastern downtown neighborhoods, the Sixth District covers the southern end of the city, the Seventh District covers the eastern side of New Orleans, and the Eighth District includes the French Quarter and the surrounding tourist and commercial areas.

Given that CIT training is voluntary it is essential to examine selection into training. Table **??** presents descriptive statistics for officers by CIT status. CIT-trained officers are more likely to be female, are younger, and less experienced than non-trained officers. I also check for selection on the dependent variable and see whether officers who select into training have a systematically different use of force and arrest propensity prior to training as compared to never-trained officers. To do this, I compare use of force and arrests rates during the year prior to the first cohort's training date. Restricting the sample to the year before the first cohort's training date provides a common pre-treatment period during which all eventually trained officers had not yet received CIT training. Figure 2 plots the use of force and arrest rates. Officers who are eventually trained had lower use of force even prior to training, indicating positive selection into treatment.

Table 4: Officer Demographics by CIT Status

	CIT-trained	Untrained	Overall
% female	0.31	0.20	0.23
% Black	0.47	0.53	0.50
Avg age	43	48	41
Avg years of experience	11	16	12

Note: Column 1 is the percent of CIT-trained officers who are female and Black, their mean age and mean years of experience. Column 2 is the percent of non-CIT-trained officers who are female and Black, their mean age and mean years of experience. Column 3 presents the average demographics for all officers.

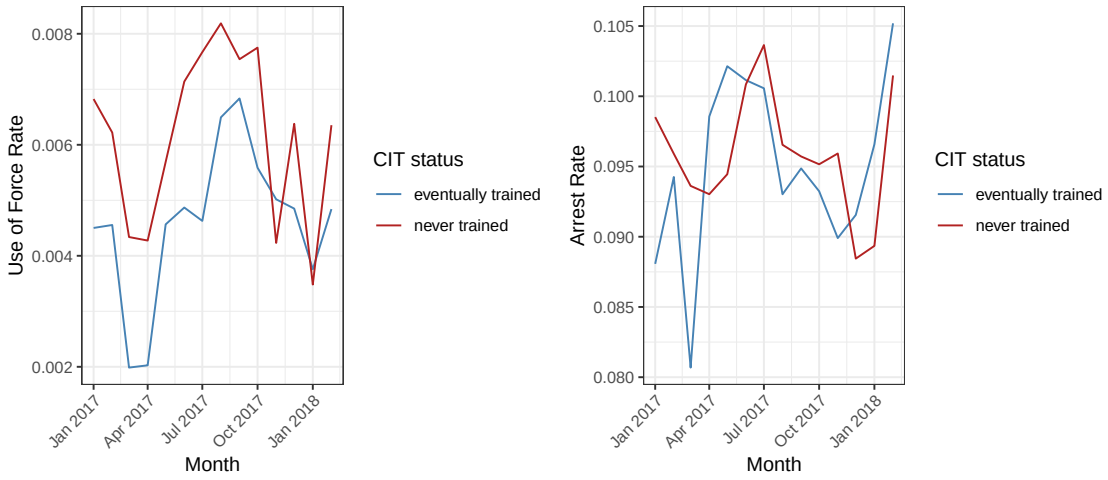

Figure 2: Selection into Treatment

Notes: This figure plots the monthly use of force (left panel) and arrest rates (right panel) for eventually-CIT-trained and never-trained officers in the year prior to the sample's first training cohort.

4 Empirical Strategy

I consider a staggered adoption design with N officers observed over T months. Let $i \in 1, \ldots, N$ index officers and $t \in 1, \ldots, T$ index months. Officers may receive CIT training at different points in time or not at all. Let G_i denote the month in which officer i completes training, with $G_i = \infty$ for officers who are never trained. Once an officer is trained, they are considered treated in all subsequent periods.

For each officer-incident, let $Y_{ict}(0)$ denote the potential outcomes without training and let $Y_{ict}(1)$ denote the potential outcome with training. Outcomes are an indicator for whether the incident results in use of force or an arrest. The object of interest is the causal effect of training on officer behavior at the incident level.

The primary challenge is that the counterfactual outcome $Y_{ict}(0)$ for treated officers is unobserved. A naive comparison of trained and untrained officers would be biased if trained officers differ systematically from untrained officers. The descriptive evidence above suggests they do differ, and so instead, I exploit variation in the timing of training across officers and compare changes in outcomes for officers before and after training to outcomes for officers who have not yet been trained. This yields a difference-in-differences design with staggered treatment timing.

I estimate the following equation:

$$Y_{ict} = \alpha_i + \gamma_t + \beta_0 Treated_{ic} + \sum_k D_{ct}^k + \sum_{k \neq 1} \beta_k \left(Treated_{ic} \cdot D_{ct}^k \right) + \epsilon_{igt} \tag{1}$$

where Y_{ict} is an indicator for whether officer i uses force or makes an arrest at incident c in month t. α_i are officer fixed effects and γ_t are calendar month fixed effects. $Treated_{ic}$ is an indicator equal to 1 if officer i received CIT training in cohort c. The variables D_{ct}^k are indicators equal to 1 if month t is k periods relative to officer i's training date in cohort c. The coefficients of interest are β_k, which capture which the difference in outcomes between treated and control officers at event time k (relative to omitted period $k = -1$). Because officers can appear in multiple cohort-specific samples, they may contribute observations as both treated and control units. To account for this dependence, I cluster standard errors at the cohort level.

This estimation strategy uses officers who are eventually given CIT training but have not yet been trained at time t as the control group for officers trained at time t, following Deshpande and Li (2019). For each

month t, I label officers who had finished training by that month as treated and use officers who are trained in the next calendar year or later as the control group in month t. In practice, I create a stacked cohort data set. For each training cohort, I construct a dataset that includes all mental health incidents involving officers trained in that cohort (treated) and officers who are trained at least one year later (controls). For example, for the cohort trained on February 23, 2018, the sample includes incidents involving those officers as well as incidents involving officers whose training occurs at least one year after that date. I then stack these cohort-specific datasets to form the final estimation sample.

The analysis sample consists of all incidents involving officers trained in February 2018 or later, corresponding to CIT training cohorts 9 through 16. I impose this restriction to ensure a sufficiently long pre-treatment period for all eventually trained officers, as the incident-level data begin in 2017.

The identifying assumption is that without training, the rates of use of force and arrest would have evolved in parallel for officers that experience training in a given cohort relative to officers that experience training in a later cohort. While this cannot be directly tested, evidence of parallel trends in months prior to training supports this. See Figure 4.

A concern is that CIT training may change the composition of calls trained officers respond to. If CIT-trained officers are assigned only to mental health incidents after training, changes in outcomes could reflect differences in exposure to these types of incidents rather than changes from training. For example, increased exposure could improve performance through experience or alter responses through fatigue. In either case, shifts in the types of calls handled could affect outcomes independently of training, which is a threat to identification. I test for changes in call composition by estimating an event-study with an indicator for mental health incidents as the outcome, including officer and shift-by-date fixed effects. Figure 3 presents the estimates. I find no evidence that the share of mental health calls within a shift changes after training.

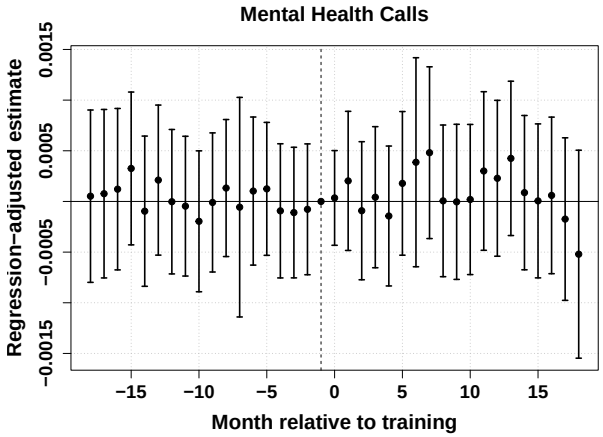

Figure 3: Mental Health Call Composition

Notes: This figure plots the event-study coefficients from a regression of a binary indicator for whether an incident was a mental health call on officer and shift-by-date fixed effects. This tests for a change in the composition of calls an officer responds to on a given shift in the months before and after receiving CIT training.

5 Results

Figure 4 presents estimates of the effect of CIT training on an officer's propensity to use force and to make an arrest. These are estimates of the β_k coefficients from Equation (2.1). For the estimates presented in Table 5 I pool all treated and u-treated periods into one pre- and one post-period.

CIT training does not appear to meaningfully affect an officer's likelihood of making an arrest or using force. While the estimates are imprecise, they do not indicate evidence of large or systematic effects. CIT training is often promoted as a key tool for improving police use of force in response to mental health

incidents. The results here do not provide evidence in support of that claim. These findings are policy relevant as many departments are investing in mental health training programs and would benefit from evidence on their effectiveness.

There are several possible explanations for these results. One possibility is that CIT training does not substantially affect arrest or use-of-force outcomes. Alternatively, the version of CIT implemented by the New Orleans Police Department may be important. Although NOPD reports following the standard Memphis Model used by many departments, I am unable to observe the content or delivery of the training directly. As a result, it is difficult to identify the mechanisms underlying the null effects. For example, the duration of training or its classroom-based format may not be sufficient to change officer behavior.

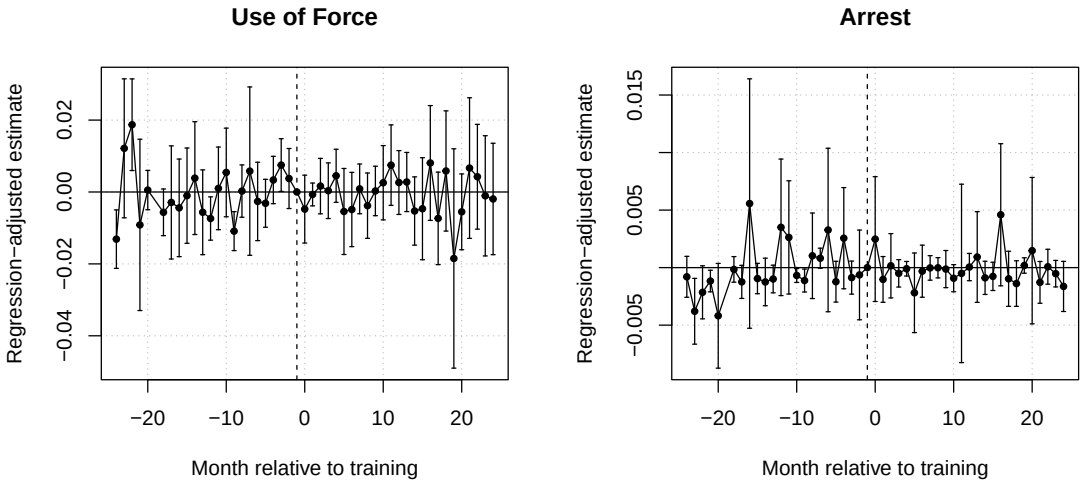

Figure 4: Use of Force and Arrest Results

Notes: This figure plots estimates of the effect of CIT training on an officer's propensity to use force (left panel) and make an arrest (right panel). These are estimates of coefficients β_k from Equation (1). The dependent variable is a binary indicator for force being used at the incident or an arrest being made. The sample is all incidents involving officers who are trained during the period of observation. Controls are yet-to-be-trained officers. The error bars plot the 95% confidence interval of the estimated coefficients.

Table 5: Pooled DiD

	Use of Force	Arrest
	(1)	(2)
Treated × Post	−0.0007	−0.0004
	(0.0018)	(0.0005)
Untreated mean	0.025	0.002
Observations	96,057	96,057

Notes: *p<0.1; **p<0.05; ***p<0.01. The estimates are for the coefficient δ from $Y_{igt} = \alpha_i + \gamma_t + \delta_0 Treated_{ig} + \sum_k D^k_{gt} + \beta\left(Treated_{ig} \times Post_{gt}\right) + \epsilon_{igt}$. Treated = 1 if the officer ever receives training and Post = 1 if the incident occurred after the officer received training. Fixed effects for incident priority, day of week, shift and district are included. The sample is only mental health incidents. Only officers who receive training during the window of observation (2017- June 2023) are included. This excludes always-treated and never-treated officers. Standard errors are clustered at the cohort level.

5.1 Spillovers

The focus of CIT training is preparing officers to respond to mental health crises, but de-escalation techniques can be easily transferable to other scenarios. While I am not able to find an effect for mental health calls, it is possible officers are using their skills on other calls. To check for possible spillovers, I perform the same analysis as above on non-mental health incidents, violent incidents, and drug-related incidents.[11] Table 6 presents the results. I find no evidence that CIT training affects use of force or arrest rates for any of these incident types. As expected, violent incidents have substantially higher baseline arrest rates, reflecting the nature of these offenses, which are more likely to result in arrest. Drug-related incidents may be more comparable to mental health calls, as they can involve similar behaviors and may also benefit from de-escalation techniques. However, I do not detect effects for these incidents either.

Table 6: Other Incident Types

	Non-Mental Health		Violent		Drug	
	Use of Force	Arrest	Use of Force	Arrest	Use of Force	Arrest
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.00003	0.0013	−0.0015	0.0014	−0.0024	−0.006
	(0.0002)	(0.0016)	(0.0015)	(0.0040)	(0.0043)	(0.0154)
Untreated mean	0.01	0.13	0.03	0.50	0.04	0.80
Observations	1,862,193	1,862,193	213,371	213,371	8,307	8,307

Notes: *p<0.1; **p<0.05; ***p<0.01. The coefficient presented is δ from Eq.(2): Treated = 1 if the officer ever receives training and Post = 1 if the incident occurred after the officer received training. Fixed effects for incident priority, day of week, shift and district are included. The sample is only mental health incidents. Only officers who receive training during the window of observation (2017- June 2023) are included. This excludes always-treated and never-treated officers. Standard errors are clustered at the cohort level.

6 Conclusion

This paper examines the impact of crisis intervention team (CIT) training on police officers' use of force and arrest behavior using data on all calls for service in New Orleans from 2017 through early 2020. I find no evidence that CIT training meaningfully affects an officer's likelihood of using force or making an arrest in response to mental health incidents. I also find no evidence of spillover effects to other types of calls.

These findings contribute to ongoing discussions about how best to respond to mental health crises. CIT training is often promoted as a key tool for improving police interactions in these contexts, but these results do not provide clear evidence that it changes key observable behaviors. Understanding why CIT training does not produce detectable effects in this setting is an important direction for future research. For example, differences in the content, duration, or delivery of training may limit its effectiveness. Additionally, because the training is voluntary, officers with lower use of force rates may be more likely to select into CIT training, potentially reducing the program's impact.

More broadly, these results highlight the importance of the implementation of reforms. CIT training was introduced in the context of the New Orleans consent decree as a mandated, top-down policy change, rather than one developed organically or accompanied by officer buy-in. These findings suggest that some reforms may be more symbolic than substantive, reflecting performative compliance rather than meaningful changes in behavior.

[11] I define violent incidents as any incident classified in CAD as an assault, battery, homicide, weapon possession, or rape. I define drug-related offenses as any incident classified in CAD as a drug violation or drunk incident.

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A Appendix

A.1 Use of Force Definition

Use of Force Definitions [12]:

1. Level 1: uses of force include pointing a firearm at a person and hand control or escort techniques (e.g., elbow grip, wrist grip, or shoulder grip) applied as pressure point compliance techniques that are not reasonably expected to cause injury; take-downs that do not result in actual injury or complaint of injury; and use of an impact weapon for non- striking purposes (e.g., prying limbs, moving or controlling a person) that does not result in actual injury or complaint of injury. It does not include escorting, touching, or handcuffing a person with minimal or no resistance.
2. Level 2: uses of force include use of a CEW (including where a CEW is fired at a person but misses); and force that causes or could reasonably be expected to cause an injury greater than transitory pain but does not rise to a Level 3 use of force.
3. Level 3: uses of force include any strike to the head (except for a strike with an impact weapon); use of impact weapons when contact is made (except to the head), regardless of injury; or the destruction of an animal.
4. Level 4: uses of force include all 'serious uses of force' as listed below
   (a) All uses of lethal force by an NOPD officer
   (b) All critical firearm discharges by an NOPD officer
   (c) All uses of force by an NOPD officer resulting in serious physical injury or requiring hospitalization
   (d) All neck holds
   (e) All uses of force by an NOPD officer resulting in a loss of consciousness
   (f) All canine bites;
   (g) More than two applications of a CEW on an individual during a single interaction, regardless of the mode or duration of the application, and whether the applications are by the same or different officers, or CEW application for 15 seconds or longer, whether continuous or consecutive
   (h) Any strike, blow, kick, CEW application, or similar use of force against a handcuffed subject
   (i) Any vehicle pursuit resulting in death, serious physical injury or injuries requiring hospitalization

A.2 Alternative Specifications

A.2.1 Static TWFE

I estimate a two-way fixed effects model at the officer-month level. An officer is marked as treated for any incident they are dispatched to after their training date, and all data is pooled into one pre-period and one post-period.

$$Y_{ict} = \alpha_i + \gamma_t + \phi Treated_{ict} + \beta X_c + \epsilon_{ict} \tag{2}$$

Y_{ict} is an indicator for whether officer i used force or made an arrest at incident c in month t. α_i are officer fixed effects and γ_t are time fixed effects. $Treated_{ict}$ is an indicator equal to one if officer i had already received CIT training by month t when responding to incident c. X_c is a vector of call characteristics including district, priority, shift, and day of week. The sample is all calls for service for mental health incidents.

The coefficient of interest is ϕ. The identifying assumptions for ϕ to provide an unbiased causal estimate of the average treatment effect are: parallel trends and constant treatment effects between groups and over time.

[12] from NOPD policy manual

In this context the parallel trends assumption would require that officers who receive CIT training and officers who never receive training would have maintained common use of force and arrest trends in the absence of treatment. To assess the validity of this assumption I plot the rates of use of force and arrest rates prior to training for officers who receiving CIT training and rates of use of force and arrest rates for officers who never do, presented in Figure A1. If we took the average the never-treated and treated officers would have very similar rates of force use and arrests in the pre-period, but by plotting the pre-trends month-by-month we see they are not parallel. Officers who select into training have higher rates of both force and arrests prior to training than the never-treated officers and the arrest trends cross, potentially violating parallel trends.

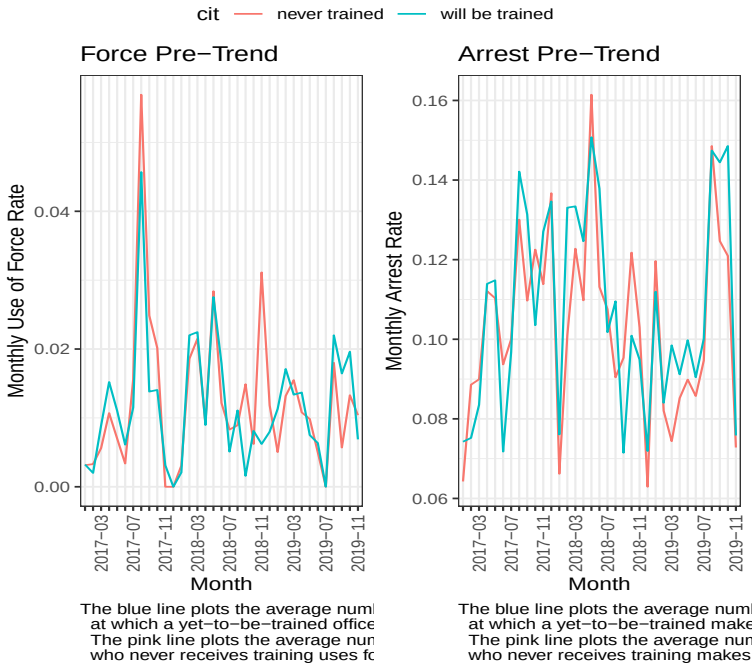


Figure A1: Pre-Trends

Notes: This figure plots the pre-treatment use of force and arrest rates of never-trained officers and trained officers. The blue line plots the average number of calls per calendar month at which an officer who will receive training uses force or makes an arrest in the months prior to training. The pink line plots the average number of calls at which an officer who was never trained uses force or makes an arrest in the same calendar month.

Table A1 presents the estimated coefficients on *Treated* from Equation (2). These estimates imply that CIT training is actually associated with an increase in use of force and propensity to arrest. However, to interpret these estimates causally we must assume constant treatment effects across cohorts and parallel trends and this may be violated.

Table A1: Static Two-way Fixed Effects

	Use of Force	Arrest
	(1)	(2)
Treated	0.005*	0.016*
	(0.002)	(0.007)
Observations	35,917	35,917

Notes: *p<0.1; **p<0.05; ***p<0.01. The coefficient presented is ϕ from Eq.(2): treated = 1 if the officer had already received training at the time of the call. Fixed effects for incident priority, day of week, shift and district are included. The sample is only mental health incidents. Standard errors are clustered at the incident level.

An additional, and related, concern is that the first CIT training cohort completed training at the beginning of 2016 but data collection did not begin until 2017, therefore I have a group of officers who are "always-treated" across my panel. To test whether always-treated officers differ from the officers whose training I observe I compare use of force and rates of arrest in the post-periods for officers who experience training in my panel and officers who are "always-treated". The plots are presented below. I also test this empirically by regressing outcomes on an indicator equal to 1 if an officer will be treated and is equal to 0 if the officer is "always-treated". The coefficient of interest for both force and arrests is insignificant.

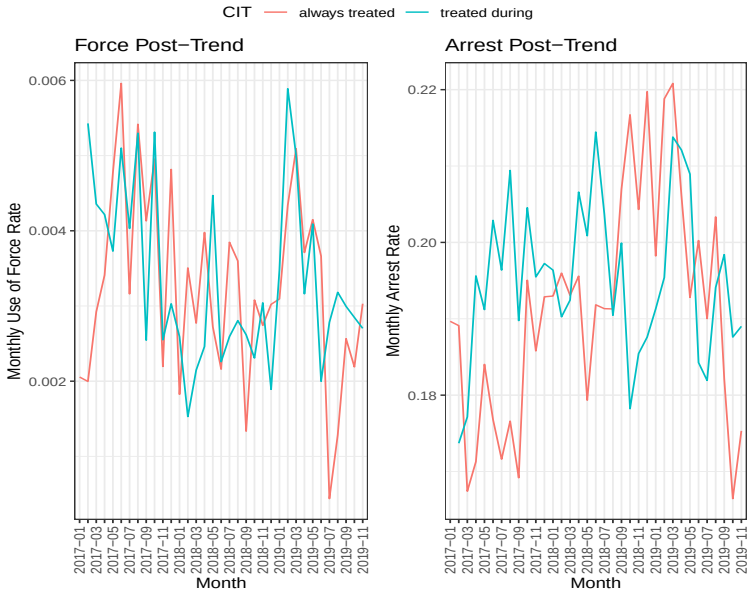


Figure A2: Always Treated vs. Eventually Treated

Notes: This figure plots the post-treatment use of force and arrest rates of always-trained officers and eventually trained officers. The blue line plots the average number of calls per calendar month at which an officer who receives training during the observation period use force or makes an arrest after they received training. The pink line plots the average number of calls at which an officer who was trained prior to the observed period uses force or makes an arrest in the same calendar month.

A.2.2 Dynamic Two-Way Fixed Effects

Next, I allow for the possibility of heterogeneous treatment effects across cohorts. CIT training had a staggered roll-out (there had been 17 training classes as of 2021) so I estimate an event-study model with two way fixed effects to allow for variation across training cohorts. I estimate the causal impact of CIT on an officer's actions with the following equation:

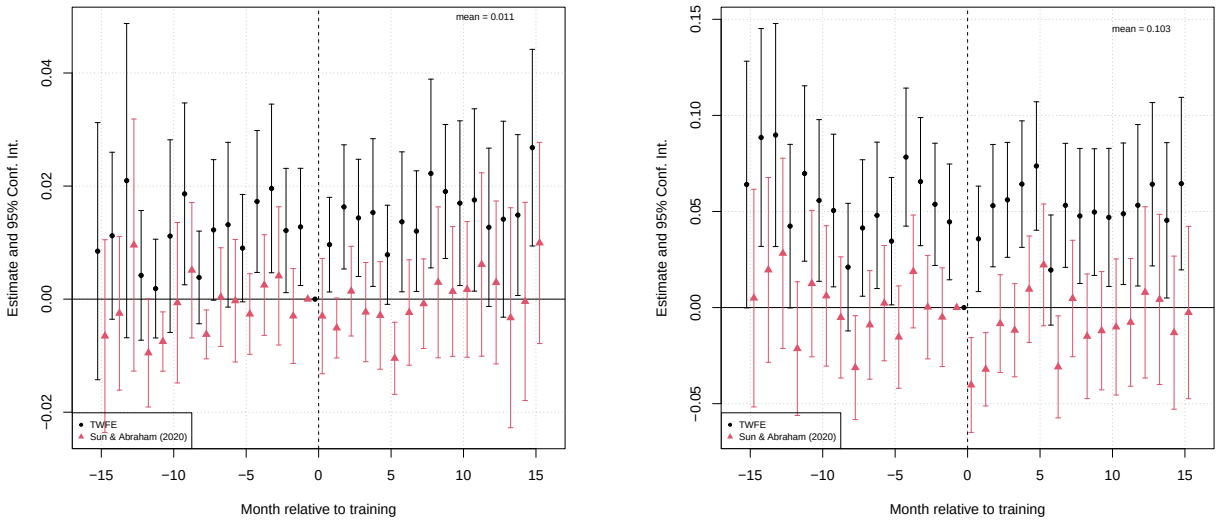
$$Y_{ict} = \alpha_i + \gamma_t + \sum_k \phi_{kt} D_{ct}^k + \beta X_c + u_{ict} \tag{3}$$

Y_{ict} is an indicator for whether officer i used force or made an arrest at call c in month t. α_i are officer fixed effects, and γ_t are time fixed effects. D_{ct}^k is an indicator equal to 1 if month t is k months after (or before) the month of training, k is negative for the months prior to training and positive for months after training. X_c is a vector of call characteristics including district, priority, shift, and day of week. The sample is all mental health incidents.

sun˙abraham provide a decomposition of the population regression coefficients ϕ_{kt}. They show that the coefficients are linear combinations of differences in trends from event period k and differences in trends from other relative periods (whether they are included or excluded from the specification). Therefore, group treatment effect estimates may suffer from possible contamination from other event-periods. They propose a method to correct for contamination from other relative periods that weights the average of cohort treatment effects by the shares of cohorts that experience at least k relative treatment periods. Under the joint assumptions of parallel trends and no anticipation the Sun and Abraham interaction-weighted estimator provides an unbiased and consistent estimate of the cohort treatment effect on the treated. CIT training is meant to provide officers with hard and soft skills for managing tense situations and so it is plausible in this scenario to assume no anticipation - just knowing they will be trained will not give them the skills required to de-escalate a volatile situation. Additionally, NOPD has indicated that training is not offered regularly but at various intervals throughout the year, meaning officers cannot predict far in advance when they will be able to sign-up for training and generally are made aware of a new training class only one month (or so) in advance.

As of 2021 there had been 17 cohorts of officers to receive CIT training (1 class in 2015, 3 in 2016, 4 in 2017, 2 in 2018, 2 in 2019, 1 in 2020, and 1 in 2021). In my data I able to observe 9 of these cohorts (2017-2020). To account for the staggered roll-out I use an event-study design. I estimate both a standard two-way fixed effects model as well as the Sun & Abraham aggregated cohort method.

I restrict the sample to 15 pre- and 15 post-periods because the sample is much larger and closer to being balanced in this restricted time frame. Focusing on the Sun & Abraham estimates that account for heterogeneous effects, there are no pretends for force or arrest and the post-trends for both are noisy around zero and so I do not find any impact on use of force or arrests. The event study plots are presented below in Figure A3.



(a) Use of Force

(b) Arrest

Figure A3: Dynamic TWFE Estimates

Notes: This figure presents the estimated coefficients from Equation B.2. The dependent variable is a binary indicator for use of force in panel (a) and arrest in panel (b). The sample is restricted to valid mental health incidents. Event time is measured relative to the month of CIT training completion (month 0). The sample includes officers trained during the observation window, never-trained officers, and always-trained officers. Standard errors are clustered at the incident level.

A.2.3 TWFE Weights

A concern from the static TWFE model is the causal interpretation of the treatment coefficient. Under the parallel trends assumption, following de Chaisemartin and D'Haultfoeuille (2020):

$$E[\phi] = E\left[\sum W_{g,t} TE_{g,t}\right]$$

where ϕ is the "overall" treatment effect and $W_{g,t}$ is the weight assigned for treatment group g at time t and $TE_{g,t}$ is the treatment effect for this group and time period. The decomposition in Goodman-Bacon (2019) shows that this may produce negative weights, especially if there are groups that are treated most or all of the time. Negative weights themselves are not necessarily an issue if there are homogeneous treatment effects, but in the case of heterogeneous effects can bias treatment effects estimates (De Chaisemartin and d'Haultfoeuille 2020, Goodman-Bacon 2018). The existence of negative weights is directly testable, as the weights placed one each observation are proportional to the residuals from a regression of treatment on unit and time fixed effects (De Chaisemartin and d'Haultfoeuille 2020)[13]. Approximately 8% of treated observations receive negative weights and these observations tend to be later months in the observation period for officers trained early[14]. As noted by Jakiela (2021) a sufficiently large never-treated group combined with sufficient pre-treatment data will ensure non-negative weights. Only 30% of officers ever receive training so a large never-treated group exists. To address point two I estimate a version of the two-way fixed effects model where I restrict my sample to officers who were never trained or were trained 6 months or more after data collection began, which naturally excludes the always-treated group. Results do not qualitatively change and are presented in the Table A2.

[13]This can be seen by applying the Frish-Waugh-Lovell theorem to a standard DiD model of the form $Y_{it} = \lambda_i + \gamma_t + \beta D_{it} + \epsilon_{it}$.

[14]Residuals are from the regression $Treated_{it} = \lambda_i + \gamma_t + \epsilon_{it}$ where i is an officer and t is a month. λ_i are officer fixed effects and γ_t are month fixed effects.

Table A2: Trimmed Panel

	All Calls		Mental Health Calls	
	Use of Force	Arrest	Use of Force	Arrest
	(1)	(2)	(3)	(4)
Treated	−0.0004	−0.0200	0.0018	0.0190
	(0.0003)	(0.002)	(0.0033)	(0.009)
Observations	370,259	370,259	11,526	11,526

Notes: *p<0.1; **p<0.05; ***p<0.01. Treated = 1 if the officer received training and the incident occurred after training was completed. Fixed effects for incident priority, day of week, shift and district are included. The top panel uses the repeated cross-section sample of all valid incidents and the bottom panel uses the sample of only mental health incidents. Only officers who never receive training or receive training 6 months or more after the observation window begins (June 2017- Feb 2020) are included. Standard errors are clustered at the incident level.

A.3 Appendix Tables

Figure A4: Top Types of Calls Resulting in Force

2017: domestic, other complaint, mental

2018: mental, domestic, other complaint

2019: mental, battery, domestic

2020: mental, domestic, prowler

2021: other complaint, suspicious person, mental

2022: suspicious person, disturbance, mental

2023*: EDP, suspicious person, weapon

Note: Sample is all calls that resulted in force between January 1, 2017 and June 30, 2023.

Table A3: Officer Demographics by Training Class

Cohort	N officers	% Female	% Black	Avg age	Avg years of service
1	20	0.3	0.55	40.15	14.25
2	21	0.29	0.57	40.95	16.76
3	19	0.32	0.47	40.11	15.89
4	27	0.52	0.63	40.04	11.96
5	22	0.23	0.55	38.86	14.82
6	23	0.35	0.39	35.39	12.39
7	16	0.06	0.06	31	5
8	27	0.22	0.41	38.37	12.56
9	25	0.32	0.36	37.2	10.92
10	23	0.35	0.43	34.65	9.48
11	15	0.2	0.27	35.85	8.93
12	14	0.29	0.5	37.07	12.5
13	21	0.33	0.62	31.42	7.24
14	22	0.36	0.45	33.6	8.95
15	17	0.47	0.65	34.31	7
16	17	0.18	0.53	37.5	5.06
17	16	0.25	0.5	32	4.19

Notes: The first five training classes took place in 2016, before data collection began. Training class 6 took place in February 2017, meaning there is only one month of pre-data and so I exclude them from analysis. Training class 7 was abnormally dominated by white men and so they are also excluded. Averages are taken at time of training.

Table A4: Officer Demographics by Shift

Shift		% Male	% Black	Avg age	Avg years of service
Between 11pm-7am	Fri	0.8	0.44	38.36	10.71
Between 11pm-7am	Mon	0.8	0.44	38.38	10.67
Between 11pm-7am	Sat	0.8	0.43	38.25	10.56
Between 11pm-7am	Sun	0.8	0.44	38.28	10.65
Between 11pm-7am	Thu	0.8	0.44	38.39	10.74
Between 11pm-7am	Tue	0.8	0.44	38.21	10.53
Between 11pm-7am	Wed	0.8	0.45	38.21	10.56
Between 3pm-11pm	Fri	0.82	0.38	36.34	8.91
Between 3pm-11pm	Mon	0.82	0.39	36.42	8.97
Between 3pm-11pm	Sat	0.81	0.37	36.16	8.74
Between 3pm-11pm	Sun	0.81	0.37	36.36	8.81
Between 3pm-11pm	Thu	0.82	0.38	36.38	9.02
Between 3pm-11pm	Tue	0.82	0.41	36.47	9.05
Between 3pm-11pm	Wed	0.82	0.39	36.3	9.02
Between 7am-3pm	Fri	0.76	0.48	39.71	11
Between 7am-3pm	Mon	0.76	0.49	39.79	10.96
Between 7am-3pm	Sat	0.76	0.46	39.51	10.76
Between 7am-3pm	Sun	0.76	0.47	39.6	10.77
Between 7am-3pm	Thu	0.76	0.49	39.79	11.09
Between 7am-3pm	Tue	0.75	0.5	39.83	11.05
Between 7am-3pm	Wed	0.76	0.5	39.83	11.14

Notes: Averages taken over 2017 - June 2023. An officer's shift is only observable if they appear as a responding officer in the CAD data during said shift. However, it would be extremely unlikely for an officer to not appear in CAD data at all during a shift and so it is unlikely an officer is missed.