**Title: Quantifying CAHOOTS: Mobile crisis response program diverts and prevents police response**

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**Abstract:** Mobile Crisis Response Programs (MCRPs) have emerged as alternatives to police for emergency mental and behavioral health calls, yet their effectiveness in diverting calls from police remains contested. CAHOOTS, the United States' longest-running MCRP, has been subject to widely varying *ad hoc* diversion rate estimates, from 3% to 20%. We use a systematic difference-in-differences design to estimate the causal effects of CAHOOTS on police call volume by introducing three estimators. The Substitution Diversion Rate (SDR) quantifies MCRP responses that directly replace police responses and estimate it as 18% for CAHOOTS. Our results show in addition to substituting for police response, CAHOOTS prevented police calls. The Prevention-adjusted Diversion Rate (PDR) accounts for this, and we estimate at 23% for CAHOOTS. Finally, the Overlapping-mandate Diversion Rate (ODR) quantifies the proportion of mutually answerable calls handled by an MCRP. We estimate CAHOOTS' ODR at 50%. Our findings provide evidence that MCRPs significantly reduce police response call volume through both direct substitution and incident prevention.

**Main Text:**

## Introduction

Since 2020, communities across the U.S. have debated the appropriate role for police in responding to mental and behavioral health crises (*1*). Mobile Crisis Response Programs (MCRPs) offer a civilian alternative, deploying mental health professionals and crisis workers instead of police officers to handle low-acuity, non-violent calls. Subsequently, these programs have gained popularity, with more than 116 now operating across the U.S.(*2*) Researchers are actively evaluating their efficacy across multiple metrics (e.g. (Denver) (*3-4*); (San Francisco) (*5*); (Portland, OR) (*6*)). Many of these programs are modeled after CAHOOTS (Crisis Assistance Helping Out On The Streets), the earliest established MCRP in the U.S. which started in Eugene, Oregon in 1989.

Research shows numerous positive impacts of MCRPs. Qualitative research finds high levels of support and satisfaction from stakeholders, community groups, institutional affiliates, and MCRP clients (7-8). Studies using administrative data to track institutional and service utilization among

MCRP clients find decreased rates of emergency room use, in-patient hospitalization, and criminal justice system involvement (9-*13*). Evidence shows that CAHOOTS response specifically results in fewer arrests and more connections to medical services, without sacrificing public safety (*14*). However, few studies answer one of the early galvanizing questions: Can MCRPs divert calls from the police? This question has important implications for how MCRPs integrate into the broader landscape of emergency response and public safety, and their potential impacts for costs, resources, and personnel.

The few studies that have explicitly examined MCRP diversion rates use measurements that are not standardized nor well-defined. One source of disagreement is the extent to which MCRPs *divert* calls typically handled by police, or provide an *additional* form of emergency response to address calls outside of the scope of police response (*6*, *15*). Still, researchers project that Denver's STAR program could divert 3% of all police calls for service (*16*), and estimate that Portland Street Response diverts 3.5% of police calls during its hours of operation (*6*). Despite being a national model for MCRPs, CAHOOTS' diversion rate has been estimated inconsistently, with reports documenting anywhere between 3-20% (*17–20*).

CAHOOTS represents the most mature case study for accurately calculating diversion rates and assessing MCRP potential. Dispatch practices significantly influence call diversion, and nascent programs often face implementation challenges: dispatchers may lack comprehensive training, exercise excessive caution when deploying unarmed crisis teams, or operate under incomplete protocols (*21*). Because CAHOOTS has been operational for over 35 years and has established deep trust and rapport with the community, it provides a crucial case for identifying the full potential for diverting calls from police to MCRPs.

In this study, we offer quasi-experimental evidence quantifying CAHOOTS diversion and prevention impacts. We propose an additional metric to estimate the proportion of mutually addressable calls handled by CAHOOTS. In the process, we critically examine a well-publicized attempt to estimate CAHOOTS diversion rates, resolving inconsistencies. As communities nationwide adopt or pilot similar models, rigorous causal research remains scarce (*4*) (although see (*14*)). With this systematic analysis of the CAHOOTS model, we offer compelling quantitative insight into the longstanding debate about MCRPs diversions of police calls. Additionally, our approach for quantifying different types of diversions can be adopted by other researchers, practitioners, and policymakers to provide stronger evidence when implementing or evaluating MCRPs.

**Diversion Rate Controversy**

When CAHOOTS entered the national spotlight in 2020, media drew attention to the program's impact, citing estimated diversion rates of 17-20% (*18*-19, *22*). However, the Eugene Police Department (EPD) challenged the validity of these figures and conducted an internal analysis (henceforth the "EPD report") with much lower estimates of 3-8% (*20*). The EPD report attributed this difference primarily to call scope, arguing the higher estimates improperly included calls outside traditional police duties which, they contended, were not genuine diversions. To remove calls outside of the police mandate, the EPD report drops call types (specifically Transport and Public Assist), or portions of call types (Welfare Check). While we accept the premise that diversion identification should be limited to calls that would merit police response, we demonstrate that the EPD report is marred by critical methodological errors, including inconsistent comparisons, inappropriate call type exclusions, a lack of methodological transparency, and data discrepancies, resulting in a systemic downward bias in diversion rate estimates (see section S2.2). When we corrected the EPD report's computational errors, even while maintaining their questionable assumptions, the diversion rate increases from their reported 8% to 14.6% (Section S2.2.2, eq. 6). Absent rigorous, scientifically validated estimates, flawed methodologies such as these inevitably gain traction as authoritative references, informing public dialogue and decision making.

**Call Type Divertibility and Prevention**

The EPD report conceptualized call type divertibility as the proportion of calls within a given type that would necessitate a police response if CAHOOTS were absent. However, the report only applied this concept to Welfare Check calls, using an unreproducible *ad hoc* method (see S2.2.3). Moreover, in addition to directly substituting for police response, CAHOOTS may also play a role in preventing some calls, as acknowledged by EPD itself (see Section S1.3) (*23*). A comprehensive diversion rate should account for both mechanisms through which an MCRP reduces police workload: direct substitution, where the MCRP responds to calls that would otherwise require police response, as well as prevention, where MCRP services reduce the occurrence of certain incidents altogether. Traditional diversion metrics generally focus on substitution effects, potentially underestimating the full impact of crisis response programs (*3*, *6*, *20*). We propose an empirical estimation of call type divertibility that captures both direct substitution and prevention.

To develop a more accurate assessment of how many calls CAHOOTS diverts from traditional police services, we leverage a natural experiment: prior to January 1, 2017, CAHOOTS was inactive between 3-7am, with a partial service expansion beginning November 1, 2016, from 7-10am (Figure 1A). By considering how call volume changed with the addition of CAHOOTS service hours, we can make inferences about how the presence of CAHOOTS interacts with the emergency response system. For call types where CAHOOTS primarily adds services distinct from police responsibilities, we expect an overall increase in calls during the newly serviced periods. This increase would be more pronounced for call types with a higher proportion of calls outside of the police mandate (that is, call types with lower divertibility). Call types with no significant call volume changes would either represent CAHOOTS substituting for EPD response, or little-to-no impact from CAHOOTS. Finally, we expect a reduction in volume for call types where CAHOOTS exerts a preventative effect.

Data were obtained from Computer Aided Dispatch (CAD) logs from the City of Eugene, Oregon via a public records request. The dataset covered the period from January 1, 2016, through January 1, 2019, and included all publicly initiated calls for service handled by either CAHOOTS or the EPD. Each record in the dataset captured details on the call type, location, dispatch status, and responding unit. CAHOOTS handles the greatest proportion of Transport, Public Assist, and Welfare Check calls but CAHOOTS still fills in gaps throughout the emergency response system (Figure 1B). Full data is available in Dryad repository [CITE].

While EPD call volumes during the expansion hours were stable between 2016 and 2017, we observe substantially higher total call volume for CAHOOTS following the 2017 expansion. (Figure 1C-D) This rise is most evident in two of the three most common CAHOOTS call types: Transport and Public Assist, but we observe little change in Welfare Checks (Figure 1 E-G). These patterns are consistent with the hypothesis that Public Assist and Transport calls often fall outside core police functions, whereas Welfare Checks are generally within the scope of both EPD and CAHOOTS.

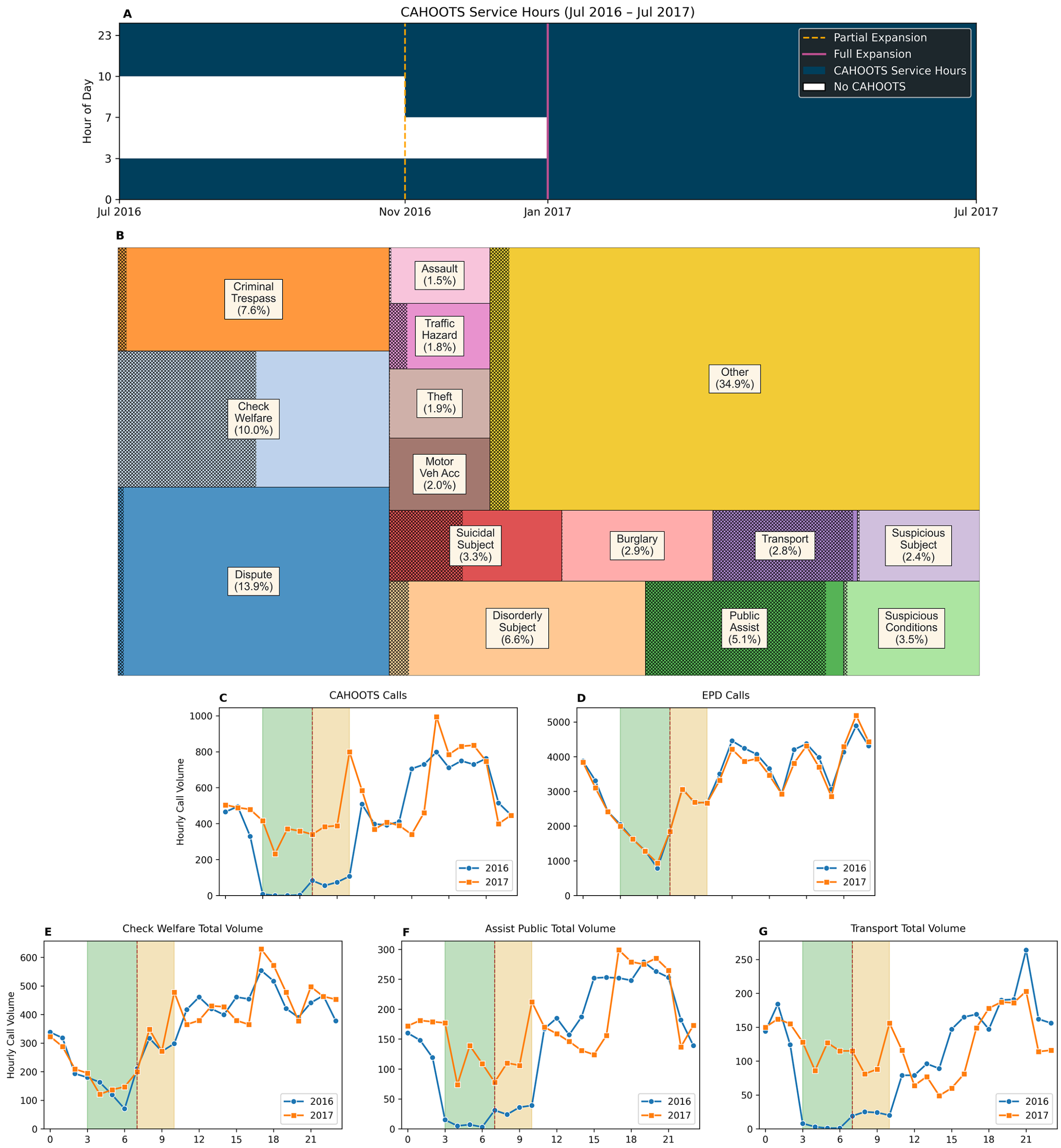

**Fig 1. CAHOOTS service expansion and call-volume patterns.** (A) The schematic shows the CAHOOTS service hours expansion. (B) The tree map visualizes the 14 most frequently dispatched call types (2017-2021). The area of each rectangle is proportional to that call type's overall frequency. Within each rectangle, the cross-hatched section indicates the proportion handled by CAHOOTS, and the solid section indicates the proportion handled by EPD. The "Other" category contains 247 unique call types. (C-G) Hourly call volumes are shown for 2016 (blue circles) and 2017 (orange squares) for (C) CAHOOTS calls, (D) EPD calls, (E) total Welfare Check calls, (F) total Public Assist calls, (G) total Transport calls. The green band indicates the full service expansion hours, with the vertical dashed line at 07:00 marking the start of the partial expansion (gold band).

### ***Substitution Diversion Rate***

To quantify call type divertibility and the preventative impact of CAHOOTS we employ a difference-in-differences (DiD) framework. We compare changes in call rates between newly serviced hours (treatment) and other times (control) before and after expansion, estimating call type-specific effects (see Supplemental Section 3). This method aims to isolate the causal impact of CAHOOTS' expanded coverage, controlling for baseline differences, citywide trends, and unequal exposure times. (Section S3.3, eq. 7)

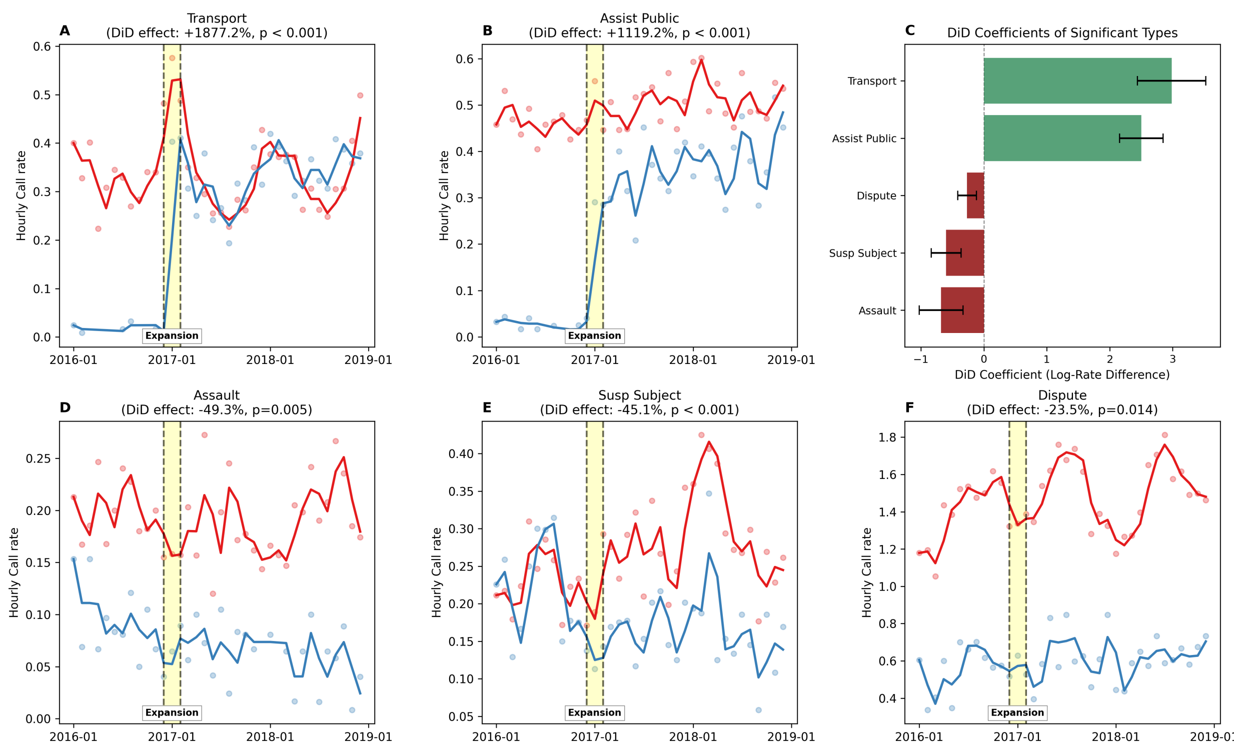


**Fig 2. Impact of CAHOOTS Service Hour Expansion on Hourly Call Rates.** DiD analysis results are shown for all call types with statistically significant volume changes following the service expansion. (A-B, D-F) show average hourly call rates by month, comparing treatment hours (3:00–7:00 AM, blue) with control hours (all other times, red). Faint points are raw monthly values. Solid lines represent a 2-month rolling average. The yellow shaded area marks

the expansion event on January 1, 2017 (±1 month). (C) DiD coefficients (log-rate difference) with 95% confidence intervals are shown with for call types with significant increases (green) and decreases (red).

After adjusting for multiple comparisons, we identified statistically significant increases in call volume during the added CAHOOTS service hours for call types Transport (1877% increase, $p < 0.001$) and Public Assist (1119% increase, $p < 0.001$) (Figure 2A-B). Effect size calculations indicate that approximately 95% (95 CI: 91%–97%) of Transport and 92% (95 CI: 88%–94%) of Public Assist calls during the newly covered hours represent additional volume attributable to CAHOOTS (Figure 2C, Section S3.6). These results strongly support the notion that CAHOOTS primarily provided additional, distinct services rather than substituting for police response within these call types. The remaining call types analyzed exhibited no statistically significant increases during expansion hours, suggesting either pure substitution, prevention or minimal CAHOOTS influence.

After removing the proportion of Transport and Public Assist calls determined to be outside of the police mandate, we find an SDR of 18% (Section S3.7, eq. 9), considerably larger than previously estimated by the EPD.

### *Prevention-adjusted Diversion Rate*

The impact of CAHOOTS extends beyond pure substitution and into prevention. Our DiD analysis also shows significant decreases in three call types traditionally handled by police during CAHOOTS expanded service hours: Assault (49.3% decrease, 95 CI: 28%–64%, $p = 0.005$), Suspicious Subject (Susp Subject) (45.1% decrease, 95 CI: 30%–57%, $p < 0.001$), and Dispute (23.5% decrease, 95 CI: 11%–34%, $p = 0.016$) (Figure 2D-F). These findings provide empirical support for the prevention hypothesis, indicating that CAHOOTS is likely reducing the volume of these majority EPD call types. While the negative direction is robust, uncertainty remains regarding the magnitude of this preventive impact, as reflected by the wide confidence intervals, particularly for Assault calls, where the effect could range from a 28% to 64% reduction (Figure 2C).

We propose the Prevention-adjusted Diversion Rate (PDR) to include all calls for service that would have been handled by police if not for the MCRP (Section S3.7). The PDR offers a more comprehensive and causally robust assessment of an MCRP's role in alleviating demand on traditional police services. We calculate CAHOOTS' PDR as 23% (Section S3.7, eq. 10). Although alternative diversion rate estimation strategies exist, the SDR and PDR are distinguished by their explicit grounding in causal inference.

## Diversions of Overlapping Mandate

The EPD reports diversion rates, along with the SDR and PDR all share a key limitation: they count police calls outside the MCRP's mandate as non-diversions. That is, calls that could only be addressed by police (like traffic enforcement) are counted as failed diversions. When including an unknown number of calls that an MCRP will never answer, the diversion rate has an unknown maximum value less than 100%. These rates are difficult to interpret particularly in a policy context, like when considering program expansion. For instance, a PDR of 8% with true ceiling of 9%, may indicate that the program is effective but further expansion may yield diminishing returns. Conversely, if the true ceiling were 20%, the same 8% would suggest significant untapped potential for growth. To address this, we propose a complementary metric: the Overlapping-mandate Diversion rate (ODR). This metric quantifies the proportion of calls handled by CAHOOTS that fall within the shared scope of both EPD and CAHOOTS.

Ideally, call-specific information about potential responding agencies would be used to determine which calls are within the overlapping mandate. However, in Eugene that information has not been collected. Instead, for this analysis, we identify these overlapping calls as those belonging to call types for which each agency independently handles at least a specified percentage of calls, a criterion we term the response parity threshold. For example, at a threshold of 0.90, both agencies must handle at least 10% of calls for a call type to qualify. A weakness of this approach is that it does not consider heterogeneity within call types for the proportion of calls that are answerable by both agencies. Still, the ODR provides a straightforward, interpretable measure (ranging from 0 to 100%) of the number of calls addressed by CAHOOTS compared to the theoretical maximum.

When considering call types in the overlapping mandate at a response parity threshold of 0.85 (Section S4), the ODR increased sharply from 36.7% in 2016 to 45.4% in 2017 (Figure 3). This jump corresponds to the expansion of CAHOOTS service hours and corroborates our earlier findings, which indicated that the expansion successfully diverted a substantial number of calls. Subsequent years saw a slower increase in ODR, with a high of 50.3% in 2021.

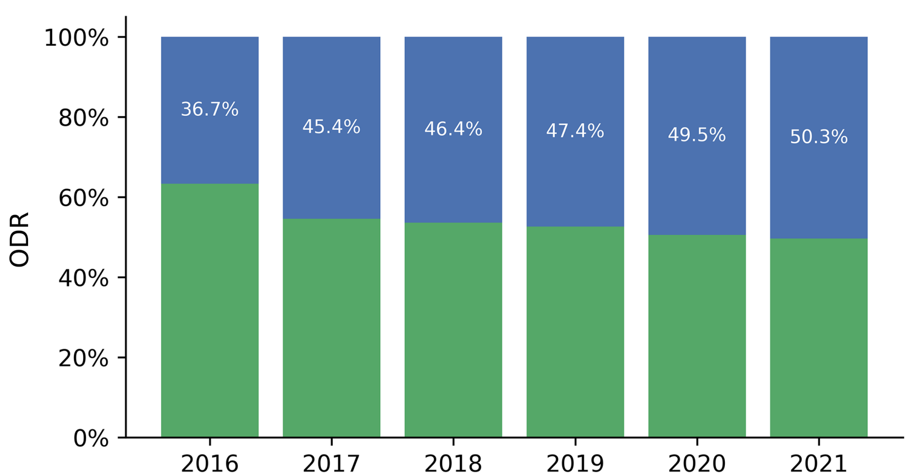


**Fig 3. ODR call types and diversion rates.** This stacked bar chart shows the annual ODR 2017-2021, with a response parity threshold of 0.85.

## Discussion

We developed evidence-based methods to estimate the SDR, PDR, and ODR to quantify how MCRP services reduce police response to emergency calls. Our SDR and PDR approaches use causal inference to account for the proportion of emergency calls answered by an MCRP that are within the police mandate. We find that the majority of CAHOOTS dispatches in new service hours are true diversions, in that they would have otherwise been addressed by EPD, in agreement with another recent study (*14*). We estimate the SDR at 18%, indicating that CAHOOTS responds to nearly one fifth of emergency calls that would have otherwise be addressed by EPD. This finding is considerably higher than the previous EPD estimates of 3-8%, which our analysis revealed to be compromised by numerous methodological and conceptual shortcomings that systematically underestimate the true rate.

Recognizing that call prevention can be conceptualized as a future diversion, we introduced the Prevention-adjusted Diversion Rate (PDR) to include police-eligible calls that were not made because of MCRP services. This metric offers a holistic estimate of the total reduction in police workload attributable to an MCRP, capturing both direct substitution and prevention effects. Applied to Eugene emergency response data, we found that CAHOOTS services are associated with significant decreases in calls for Assault, Suspicious Subject, and Dispute, call types predominantly handled by EPD. These findings provide strong empirical support for the preventative impact of CAHOOTS, aligning with anecdotal observations, including those from EPD leadership (*23*). We estimate CAHOOTS' PDR as 23%. Nearly a quarter of publicly initiated dispatched EPD calls are effectively handled or prevented by CAHOOTS. However, while this diversion rate is useful to quantify the amount of EPD workload savings, its denominator includes EPD calls that are not eligible for CAHOOTS response, resulting in an unknown maximum value, making it difficult to interpret. Therefore, we propose an additional measure, the Overlapping-mandate Diversion Rate (ODR) which only considers call types that are within the scope of service for both EPD and CAHOOTS. We estimate the ODR to be 45-50%, suggesting that of calls that could be answered by either agency, CAHOOTS handled nearly half. Both the PDR and ODR are useful measures of diversion rate; the specific rate computed should be chosen based on the question being addressed.

We acknowledge several analytical limitations and avenues for future research. Our quasi-experimental DiD approach is constrained by a pre-expansion baseline of only one year (2016), precluding robust pre-period placebo testing. While the DiD design controls for time-invariant confounders and overall temporal trends, the quasi-experimental approach leaves room for the unlikely possibility of an unobserved confounding factor coinciding with the expansion date and treatment time period (3-7am). When we use call type divertibility and prevention estimates from the DiD analysis to estimate SDR and PDR, we assume that those figures are invariant over time of day. If that is not true, there may be a bias in those estimates. Additionally, the analysis depends on dispatcher classifications of calls. If dispatchers assign call types differently depending on the responding agency, then our call type divertibility and prevention estimates may not be accurate. While we don't see evidence of notable call classification differences (see section S3.5 and table S3), we advocate for both better tracking of per-call agency eligibility (like has been done in some municipalities (*15*)), as well as social scientific research on dispatcher decisions in places with MCRPs. Finally, the way ODR is operationalized here is limited by its binary inclusion of call types based on observed response shares. A more robust implementation would quantify the proportion of calls within each type that fall within the overlapping mandate.

Future research on diversion rates should also consider the extent to which MCRPs can divert or prevent calls from EMS or possibly even fire. For example, CAHOOTS has the ability to transport clients and provide basic medical care, which may divert or prevent EMS calls. At the same time, research suggests that, compared to police, CAHOOTS response is more likely to result in EMS care, likely because of improved training to distinguish medical versus behavioral health problems (*14*). In this way, CAHOOTS service might increase EMS calls to address otherwise unmet medical needs.

In the years since MCRPs – and CAHOOTS specifically – gained widespread attention, national conversation increasingly recognizes problems with relying on police to solve persistent social challenges for which they do not have the training, resources, nor time. Specifically, police personnel are often frustrated by and unsuited to address public “disorder” related to homelessness, substance use disorder, and mental health crises (*24*). The methods we proposed to estimate three different types of diversion rates can be used to understand emergency response actions across agencies in a given community, and thereby inform efficient and effective distribution of resources. This research shows that MCRPs like CAHOOTS are an integral part of promoting public safety, likely because their organizational model and training positions them to effectively address root problems that manifest as public disorder and contribute to public safety concerns. Indeed, the CAHOOTS PDR suggests that, when mobile crisis responders address these low-level signs of disorder instead of police, there are fewer escalated incidents and public safety improves.

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Visualization: NB

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**Supplementary Materials:**

Supplementary Text

Figure S1

Tables S1 to S9

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# Supplement

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# 1. Introduction

## 1.1 Mobile Crisis Response Programs: Background and Social Context

Although Mobile Crisis Response Programs (MCRPs) initially rose to prominence in the United States during Black Lives Matter protests and nationwide movements to redirect law enforcement funding, discussions about these programs over the past five years have become increasingly intertwined with broader national anxieties regarding public "disorder" linked to growing unsheltered homelessness, mental health crises, and substance use issues. Several MCRPs – including those modeled after CAHOOTS – have been created with the aim of responding to calls and concerns about people experiencing homelessness. Some MCRP evaluations examine their effects on both homeless populations and the neighborhoods where they reside (*25, 2, 26*). Thus, while some of the early national momentum for MCRPs emerged from concerns about police violence and racial discrimination, MCRPs can also play a role in increasing access to trained crisis workers, connecting vulnerable people with appropriate services and care, and improving public safety in various contexts across the country.

In the United States, there are three primary models of alternative MCRPs. CAHOOTS fits the Community Responder model, which pairs a behavioral health specialist and an EMT, operating without law enforcement on their team. However, the Community Responder model may still often be dispatched with police or request police backup when needed. The other two common MCR models both include police officers on the responder team. Crisis Intervention Teams (CITs) are specialized police units comprised of officers who have done a minimum of 40 hours of specialized training in responding to behavioral health crises. The Co-Responder model pairs a police officer with a trained behavioral health clinician or social worker to respond in tandem to certain call types (*4, 27,* 28). CITs are criticized as "largely ineffective"(*4*) while co-responder models haven't been evaluated in-depth (*28*). Because both the CITs and Co-Responder models rely on police officers, it is not as useful to calculate rates of diversion from police and therefore aren't discussed further here.

## 1.2 CAHOOTS as a case study

CAHOOTS is particularly well suited for study as a long-standing MCRP with over three decades of operation since its 1989 founding. Newer MCRPs may still be impacted by variability in community awareness and dispatcher comfort with sending an MCRP. Because of CAHOOTS history in the city, dispatchers and police in Eugene (and neighboring Springfield) are already very experienced in determining what kind of calls CAHOOTS can handle. Community members are also well-aware of CAHOOTS and frequently request CAHOOTS directly in 911 calls, thereby removing the potential impact of new dispatch practices or lack of community-level familiarity on diversion rates.

### 1.2.1 Relationship between CAHOOTS and Eugene Police Department

The CAHOOTS case study is particularly useful due to the program's longstanding collaboration with the EPD. In this context, the EPD report's underestimation of CAHOOTS' diversion rate could suggest a kind of defensiveness on the part of police. However, CAHOOTS was designed, as the acronym suggests, to work independently yet collaboratively with police and has done so for decades. The reality is that police are expected to solve problems that they do not have the training, resources, nor time to address. For example, in places like Eugene with high rates of homelessness, residents and businesses frequently contact police about unhoused individuals sleeping or parking in public spaces, and police have expressed immense frustration with being expected to solve what is at root a structural problem in the housing market (*7*).

Individually, Eugene police officers have reported not being able to imagine doing policework without CAHOOTS, recognizing that their uniform alone can be an impediment for some people (*29*). Others even suggest observing CAHOOTS' preventative impact for public safety. In an interview about CAHOOTS, Eugene Police Chief Chris Skinner stated, "They're a tremendous crime-prevention and call-prevention tool… It's hard to predict how many calls for service they prevent us from having to go to. Say there's a guy half-clothed, screaming at people. No crime has been committed; it's just concerning. Left unaddressed, those have a tendency to escalate to the point where there's a threat of violence and then we do have to go." (*9*) This history of collaboration makes CAHOOTS an important model for assessing the broader impact of MCRPs.

## 1.3 The role of MCRPs in call/crime prevention

The "broken windows policing" theory is frequently invoked in public discussions to link minor disorder with overall public safety concerns (*30*). According to this theory, low-level signs of disorder like graffiti, public intoxication, and petty theft signal apathy and lack of social cohesion on the part of neighborhood residents, which thereby communicates to potential criminals that larger-level, violent crime is permissible and may go unpunished. Broken windows suggests that crime prevention happens through a kind of public signaling process wherein police consistently and harshly respond to and punish low-level signs of disorder, fueling "zero tolerance" and "stop and frisk" policing in cities across the U.S. (*31*, *32*). This theory is widely criticized, and its underlying logic is deeply flawed, but its impact on law enforcement across the county has been immense (*33–35*).

In contrast, the logic of MCRPs suggests that call prevention may operate through two pathways: 1) early intervention, where MCRPs address incidents outside police responsibilities, preventing escalation into the scope of police response, and 2) broader prevention, where proactive social and mental health services reduce underlying issues that may otherwise lead to incidents within the scope of police response. From one view, these pathways seem to actually reinforce part of the logic of broken windows – the idea that low-level "disorder" can escalate into criminal behavior – however, the broader mechanism of prevention is entirely different. Broken windows presumes that the signal-effect of harsh, zero-tolerance policing deters individuals from choosing to engage in criminal and/or violent behavior, whereas our analysis of CAHOOTS suggests that providing early support to meet social, mental, or behavioral needs may prevent their escalation and thereby positively influence public safety.

These prevention pathways are consistent with research evaluating the impact of the Denver STAR program which is a MCRP modeled after CAHOOTS (*16*) and Seattle's LEAD program, which includes MCRP elements but extends its reach both earlier and later in the intervention timeline. By diverting calls from police, connecting with high-need "disorderly subjects" – often people living unhoused in Seattle's business districts – before public behavioral problems emerge, and using these connections to promote service-engagement, LEAD participants have decreased criminal justice system involvement and increased rates of being sheltered, employed, and connected with income or other benefits (*4*, *36*-37).

# 2. The EPD Report

## 2.1 Background

The EPD report was prepared by the EPD Crime Analysis Unit, covering the period from January 1st, 2021, through December 31st, 2021 (*19*). The dataset used in the EPD report was constructed using proprietary data analysis tools (the CAHOOTS tool and the Annual Stats tool) that enable interactive querying and visualization of Computer-Aided Dispatch (CAD) data. Although the raw CAD data is accessible through public records requests, the analytical tools used in the EPD report are not publicly available and are housed within a closed EPD network.

While the diversion rates are the primary focus of the EPD analysis, the EPD report also provides insights into the frequency of requests for backup and the public demand for CAHOOTS services. For the purposes of this paper, we restrict our analysis to the sections pertaining specifically to diversion rates.

The EPD report provides several estimates under different assumptions of dispatch status and call type inclusion. To navigate the various calculations, we adopt a standardized nomenclature: **[Call Type]-[Numerator Dispatch Status]/[Denominator Dispatch Status]**. The EPD report uses three categories of call type inclusion (detailed in Table S1): Unadjusted (UN), including all call types; Presumed Police Mandate (PPM), excluding Public Assist, Transport, and Welfare Checks; and 74% Welfare Check (WC74), a specific adjustment that only considers 74% of Welfare Checks (See section S2.2.2).

**Table S1: Call Type Inclusion Notation**

| Notation | Category | Description |
|---|---|---|
| UN | Unadjusted | Includes all call types |
| PPM | Presumed Police Mandate | Excludes call types EPD claims are non-police |
| WC74 | 74% of Welfare Checks | Only includes 74% of welfare checks |

The EPD report also examines three dispatch status categories (detailed in table S2): Total calls (T), which encompasses all publicly initiated calls for service regardless of dispatch status; Dispatched calls (D), which requires unit assignment but not arrival; and Arrived Solo CAHOOTS (A), which requires both dispatch and arrival of a CAHOOTS unit without assistance from other agencies.

**Table S2: Dispatch Status Notation**

| Notation | Description |
|---|---|
| T | Total calls |
| D | Dispatched calls |
| A | Arrived Solo CAHOOTS calls |

We denote a particular diversion rate using [Call Type]-[Numerator Status]/[Denominator Status]. For example, UN-D/D represents the diversion rate calculated using all call types (Unadjusted), comparing Dispatched CAHOOTS calls (numerator) to total Dispatched calls (denominator).

To calculate **diversion rates**, the EPD derive serval tables from the Eugene CAD data (reproduced here). Tables S3, S4, and S5 break down CAHOOTS activity by call type and dispatch status, while Table S6 aggregates total EPD and CAHOOTS call volume.

**Table S3. 2021 Total CAHOOTS CAD Associations**

| Rank | Nature | Count | Percent |
|---|---|---|---|
| **1** | Check Welfare | 7323 | 33.2% |
| **2** | Public Assist | 7157 | 32.5% |
| **3** | Transport | 2329 | 10.6% |
| **4** | Suicidal Subject | 1631 | 7.40% |
| **5** | Disorderly Subject | 569 | 2.58% |
| **6** | Traffic Hazard | 392 | 1.78% |
| **7** | Criminal Trespass | 376 | 1.70% |
| **8** | Dispute | 298 | 1.35% |
| **9** | Found Syringe | 290 | 1.31% |
| **10** | Intoxicated Subject | 277 | 1.26% |
| **11** | Other (108) | 1413 | 6.41% |
| | Total | 22055 | |

*(Figure 1 in the EPD Report)*

**Table S4. 2021 Total CAHOOTS Dispatched calls**

| Rank | Nature | Count | Percent |
|---|---|---|---|
| **1** | Check Welfare | 6003 | 33.2% |
| **2** | Assist Public | 5788 | 32.0% |
| **3** | Transport | 1803 | 9.96% |
| **4** | Suicidal Subject | 1571 | 8.68% |
| **5** | Disorderly Subject | 457 | 2.52% |
| **6** | Traffic Hazard | 372 | 2.05% |
| **7** | Dispute | 255 | 1.41% |
| **8** | Criminal Trespass | 230 | 1.27% |
| **9** | Intoxicated Subject | 219 | 1.21% |
| **10** | Found Syringe | 192 | 1.06% |
| **11** | Other (97) | 1216 | 6.72% |
| | Total | 18106 | |

*(figure 2 in the EPD report)*

**Table S5. 2021 CAHOOTS Arrived Only Response**

| Rank | Nature | Count | Percent |
|---|---|---|---|
| **1** | Assist Public | 5058 | 33.2% |
| **2** | Check Welfare | 5022 | 32.0% |
| **3** | Transport | 1587 | 9.96% |
| **4** | Suicidal Subject | 1111 | 8.68% |
| **5** | Traffic Hazard | 280 | 2.52% |
| **6** | Disorderly Subject | 197 | 2.05% |
| **7** | Intoxicated Subject | 184 | 1.41% |
| **8** | Found Syringe | 156 | 1.27% |
| **9** | Assist Fire Dep | 156 | 1.21% |
| **10** | Disoriented Subject | 115 | 1.06% |
| **11** | Other (52) | 346 | 6.72% |
| | Total | 14212 | |

*(figure 5 in the EPD report)*

**Table S6. 2021 Combined Total calls**

| Rank | Nature | Count | Percent | %Disp'd |
|---|---|---|---|---|
| **1** | Check Welfare | 10263 | 9.3% | 84.4% |

| | | | | |
|---|---|---|---|---|
| **2** | Assist Public | 7663 | 7.0% | 79.4% |
| **3** | Dispute | 6908 | 6.3% | 93.3% |
| **4** | Criminal Trespass | 6775 | 6.2% | 73.4% |
| **5** | Beat Information | 5936 | 5.4% | 81.7% |
| **6** | Disorderly Subject | 4239 | 3.9% | 84.8% |
| **7** | Theft | 3437 | 3.1% | 26.5% |
| **8** | Illegal Camping | 2997 | 2.7% | 2.9% |
| **9** | Theft from Veh | 2624 | 2.4% | 4.0% |
| **10** | Information | 2494 | 2.3% | 5.3% |
| **11** | Other (243) | 56518 | 51.4% | 57.7% |
| | Total | 109854 | | |

*(figure 8 in the EPD report)*

### 1.1.1 Unadjusted Diversion Rate Calculations

The EPD's analysis begins by calculating the Unadjusted (UN) diversion rates. These rates (UN-T/T, UN-D/T, and UN-A/T) are derived by comparing the respective CAHOOTS activity counts from Tables S3, S4, and S5 against the total combined EPD and CAHOOTS call volume presented in Table S6, which serves as the denominator (T) for this initial set of calculations. *"If we incorrectly assume that ALL calls associated with ([table S3]: 22,055), dispatched to ([table S4]: 18,106), or handled by only CAHOOTS ([table S5]: 14,212) would be dispatched to police if CAHOOTS services were not available, then we have gross divert rates of: ~20%, ~16%, or ~12% respectively."* (*19*)

Using the EPD data tables, we replicate the calculations for these diversion rates:

$$\text{UN-T/T}=\frac{C_T}{T} = \frac{22{,}055}{109{,}854} = 0.2008$$

$$\text{UN-D/T} = \frac{C_D}{T} = \frac{18{,}106}{109{,}854} = 0.1648$$

$$\text{UN-A/T} = \frac{C_A}{T} = \frac{14{,}212}{109{,}854} = 0.1294$$

Here, $C_T$ represents all CAHOOTS calls regardless of dispatch status. $C_D$ represents all CAHOOTS calls where a unit is dispatched (18,106 calls). $C_A$ represents all CAHOOTS calls where a unit physically arrives on scene, without the assistance of other agencies (14,212 calls). T represents total calls volume regardless of dispatch status (109,854 calls). The UN-T/T rate corresponds to the 20% figure quoted in the press. (*20*, *21*). The EPD report contends that these diversion rates are methodologically flawed due to their inclusion of call types outside the standard police mandate. To combat this perceived inflation through extraneous call types, the EPD introduces the PPM diversion rates.

### 2.1.2 PPM Diversion Rate Calculations

The PPM diversion rates were calculated after excluding the three most frequent CAHOOTS call types (Public Assist, Transportation, and Welfare Check calls), operating under the assumption that the remaining call types constitute the only legitimate diversions. "*However, as discussed when examining call natures, the top 3 CAHOOTS [calls] natures:  Assist Public (5,058), Check Welfare (5,022), and Transport (1,587) are not traditionally law enforcement calls and would likely not be dispatched to police.*" (*19*) The numbers of calls for these top three incident types are sourced directly from Table S5 indicating that this diversion rate calculation is based solely on calls where CAHOOTS arrived on scene independently. The EPD report continues: "*If all calls in the top three [calls] which are CAHOOTS-centric (11,667 sum from above), are removed from the total of CAHOOTS only responses, we are left with 2,545 [calls] ([table S5] – 11,667), which are likely diverts. This equates to an overall divert rate of ~2%.*" (*19*) Note that 11,667 is the sum of the top three arrived-solo CAHOOTS call types. Thus, the calculation presented in the EPD report was:

$$\text{PMM-A/T} = \frac{C_A - R_A}{T} = \frac{2{,}545}{109{,}854} = 0.02316$$

Here, $R_A$ is a subset of those solo arrival calls, specifically those categorized as Welfare Check, Public Assist, or Transport, which the EPD argue are non-police calls (11,667 calls).

The EPD report calculates an additional PPM diversion rate analyzing dispatched calls. "*If we look only at dispatched calls for both agencies (68,427) and subtract out the removed CAHOOTS natures (11,667) we are left with 56,760 total dispatched [calls], of which 2,545 were handled by CAHOOTS, which would equate to ~4% divert rate of dispatched calls.*" Recall that 11,667 is derived from arrived calls, rather than dispatched calls, implying that not all CAHOOTS calls within the top three incident types are subtracted from the denominator. Thus, the calculation in the EPD report was:

$$\text{PPM-A/D} = \frac{C_A - R_A}{D - R_A} = \frac{14{,}212 - 11{,}667}{68{,}427 - 11{,}667} = 0.0448 \tag{1}$$

Here, D represents the total volume of calls for service dispatched to either CAHOOTS or EPD (68,427 calls).

The PPM diversion rates are mostly used as an intermediate step by the EPD report, which acknowledges that the unilateral exclusion of Welfare Checks is an unreasonable deflation. In fact, according to our overlapping mandate methodology, Welfare Checks are the largest source of diversion in the entire system (Section S4.1).

### 2.1.3 EPD Report WC74 Diversion Rates

In its final diversion rate analysis, the EPD report introduces the WC74 methodology to arrive at the final reported range of 3-8%. The EPD report acknowledges that Welfare Checks are often within the scope of both the EPD and CAHOOTS and cite an internal analysis that aims to quantify their divertible proportion: "*Check Welfare calls, handled solely by CAHOOTS, are the most challenging call nature to differentiate from traditional law enforcement [calls]. A 2019* *analysis of a random sample of 200 Check Welfare calls by dispatchers, estimated that approximately 74% (148 of 200) of these types of calls would likely be dispatched to police if CAHOOTS resources weren't available.*" (*19*) The analysis isolates Welfare Checks and applies a 74% inclusion criterion (WC74). This approach marks a major, unexplained departure from the PPM methodology, as it considers *only* this portion of Welfare Checks divertible and discards *all other* previously included PPM call types. The report calculates the final rates (WC74-D/T, WC74-D/D) based exclusively on this subset of Welfare Checks, leading directly to the 3% to 8% estimate. Notably absent is any justification for why call types previously treated as divertible were eliminated in this final calculation. The EPD report states "*If we apply this percentage to the larger group of Check Welfare [calls] dispatched to CAHOOTS in 2021 (5,546), we are left with 4,104 calls that may be sent to police (diverts). Using this methodology, the number of divert calls for CAHOOTS has remained steady year-over-year, ranging between 3% and 8%, for overall and dispatched [calls], respectively.*" (*19*).

$$\text{WC74-D/T} = \frac{C_{Dwc74}}{T} = \frac{4{,}104}{109{,}854} = 0.0374 \tag{2}$$

$$\text{WC74-D/D} = \frac{C_{Dwc74}}{D-(C_D-C_{Dwc74})} = \frac{4{,}104}{68{,}427-\left(18{,}106-(4{,}104)\right)} = 0.0754 \tag{3}$$

Here, $C_{Dwc74}$ represents 74% of CAHOOTS welfare check calls where a unit is dispatched (4,104 calls).

Our calculations mirror the methodology in the PPM diversion rates, where adjustments are made to exclude the removed call types from the denominator. Without these adjustments, the result of 4,104 divided by 68,427 would yield approximately 5.9%, which deviates from the reported 8%, so the same adjustment logic was clearly used for both metrics.

## 2.2 Methodological Problems

Having outlined the EPD Report's approach to calculating diversion rates, we now highlight significant failures of methodological rigor. Drawing directly from the text and data tables of the EPD report, our assessment reveals significant flaws that cast doubt on the validity of its findings and demonstrate a consistent downward bias in diversion estimates.

### 2.2.1 Inconsistent Comparison Types

Multiple diversion rates in the EPD paper use inconsistent comparison types without justification. A noteworthy example comes from the presumed police mandate diversion rates mentioned above. The PPM-A/D diversion rate employs asymmetric criteria in its calculation [eq.1]. The numerator consists exclusively of calls where CAHOOTS units physically arrived and operated independently, while the denominator encompasses all dispatched calls for both police and CAHOOTS (excluding non-PPM CAHOOTS calls). This methodological inconsistency, where the numerator applies more restrictive criteria than the denominator, produces a misleadingly deflated estimate compared to what would be obtained using consistent criteria across both terms. Additionally, Both the numerator and denominator are adjusted by subtracting the sum of the top three Arrived Only CAHOOTS call types, despite the denominator including dispatched calls without arrival requirements. These asymmetric comparisons simultaneously understate the numerator while overstating the denominator. This approach erroneously categorizes non-arriving Dispatched CAHOOTS calls as police-handled calls, even in cases without police involvement. In the absence of explicit methodological justification for comparing these incongruous call type classifications, we interpret this as an error.

To illustrate the impact of this error, we recalculate the diversion rate using the EPD's data tables. We modify both the numerator to include all dispatched calls and adjust both terms using dispatched rather than arrived only calls. This revised calculation yields a diversion rate of 8.2%, nearly double the EPD report's estimate of 4.48%.

$$\text{PPM-D/D} = \frac{C_D - R_D}{D - R_D} = \frac{18{,}106 - 13{,}594}{68{,}427 - 13{,}594} = 0.0823 \qquad (4)$$

Here, $R_D$ is a subset of those dispatched calls, specifically those categorized as Welfare Check, Public Assist, or Transport, which the EPD argue are non-police calls (13,594 calls).

### 2.2.2 Inappropriate Exclusion

The EPD report's call type inclusion methodology demonstrates internal inconsistencies with its stated objectives. The WC74-D/T and WC74-D/D calculations, designed to account for the partial divertibility of Welfare Check calls, implements a methodology where a subset of Welfare Checks constitute the only divertible calls (eq. 2-3).

This approach contradicts the previous PPM methodology by reclassifying all previously divertible call types as non-divertible. The EPD report provides no justification for this exclusion, simply citing the high degree of operational overlap between EPD and CAHOOTS in Welfare Check responses to apply the 74% adjustment. The exclusive classification of Welfare Checks as the sole divertible call type does not follow from the stated reasoning. Given that this methodological approach appears disconnected from the report's stated rationale, we imagine that this exclusion of previously divertible call types was an error.

Analytical choices about the eligibility of different call types for diversion dramatically change the reported rates. To demonstrate this effect, we recalculated the WC74 diversion rates while incorporating call types previously classified as divertible under the PPM methodology. Our revised WC74 calculations include 74% of Welfare Checks along with all call types except Public Assist and Transportation. While the complete exclusion of Public Assist and Transportation calls from diversion eligibility bears examination, we accept this assumption for the purpose of the WC74 diversion rate calculation. With this correction, we compute the WC74-D/T, and WC74-D/D diversion rates as 8 and 15%, respectively, as compared to 3 and 8% in the EPD report with the inappropriate call type exclusion error. If the EPD Report had correctly implemented their stated methodology, this would have been the final range of the paper.

$$\text{WC74-D/T} = \frac{C_{Dwc74} + (C_D - R_D)}{T} = \frac{4{,}104 + (18{,}106 - 13{,}594)}{109{,}854} = 0.0784 \qquad (5)$$

$$\text{WC74-D/D} = \frac{C_{Dwc74}+(C_D-R_D)}{D-(R_D-C_{Dwc74})} = \frac{4{,}104+(18{,}106-13{,}594)}{68{,}427-(13{,}594-4{,}104)} = 0.146 \tag{6}$$

It is important to note that the low range estimate still exhibits an invalid comparison, but we maintain this limitation to isolate the specific effect of inappropriate call type exclusion on the final range.

### 2.2.3 Methodological Opacity

The divertible proportion of welfare checks is fundamental to the EPD's diversion rate calculations. The EPD report contains only a single sentence describing their approach to estimating Welfare Check divertibility: "*A 2019 analysis of a random sample of 200 Check Welfare calls by dispatchers, estimated that approximately 74% (148 of 200) of these types of calls would likely be dispatched to police if CAHOOTS resources weren't available.*" (*19*) It is entirely possible that this study was conducted with utmost rigor. However, we cannot confirm this because the methodological details are not published, and the description offered by the EPD lacks sufficient detail. For instance, the number and experiences of dispatchers, the experimental scheme, which dispatchers classified which calls, the specific questions asked of the dispatchers, the variance of police mandate rates across dispatchers, time, day, season, etc. It is also not clear that querying the subjective assessment of a sample of dispatchers is an appropriate way to assess whether calls are within the police mandate. Without further disclosure, it is impossible to confirm or specifically challenge this estimate. In section S3, we discuss an alternative approach to estimating the proportion of divertible Welfare Check calls.

### 2.2.4 Data Discrepancies

The EPD report presents conflicting data in key areas of diversion rate calculation. The EPD report presents two different figures for the number of dispatched CAHOOTS Welfare Checks: 6,003 in Table S4, and 5,546 in the calculation of the WC74 diversion rates, where it states *"If we apply this percentage to the larger group of Check Welfare [calls] dispatched to CAHOOTS in 2021 (5,546), we are left with 4,104 [calls] that may be sent to police (diverts)."* This discrepancy could be attributed to a one-time error; however, the 5,546 figure reappears elsewhere in the EPD report. In a brief summary of the top three CAHOOTS call natures, the EPD lists the dispatched totals for each as: "*ASSIST PUBLIC - POLICE (5,791 dispatched),*" "*CHECK WELFARE (5,546 dispatched),*" and "*TRANSPORT (1,781 dispatched).*" (*19*) None of these numbers match the corresponding data in any of the EPD report's tables. Our replication of the WC74 diversion rates produced values of 0.037 and 0.075 (Eq. 2 & 3). The EPD report presents this range as 3-8% which raises serious methodological concerns. Rounding 0.037 down to 3% while rounding 0.075 up to 8% would be an odd decision, given that every other diversion rate the EPD presents is truncated at the decimal (which is its own unusual interpretive decision). For example, in the EPD report, the diversion rate UN-A/T of 0.12946 was reported as 12%. If we rerun the calculations for the WC74 diversion rates, using the number of dispatched Welfare Checks from Table S4 (6,003) we get:

$$\text{Updated } \mathrm{C}_{\mathrm{Dwc74}} = 6{,}003 \times 0.74 = 4{,}442.22$$

$$\text{WC74-D/T} = \frac{C_{Dwc74}}{T} = \frac{4{,}442.22}{109{,}854} = 0.0404$$

$$\text{WC74-D/D} = \frac{C_{Dwc74}}{D-(C_D - C_{Dwc74})} = \frac{4{,}442.22}{68{,}427-(18{,}106-(4{,}442.22))} = 0.0811$$

These updated calculations reveal a critical issue: while the high-end estimate is now in line with the EPD's reported figure (0.0811), the low-end estimate becomes incompatible (0.0404); no rounding convention could justify reporting 0.0404 as 3%.

Although the exact cause of these inconsistencies remains speculative, the implications are clear: using 5,546 results in a diversion rate range that does not align with the reported high-end estimate in the paper, while using 6,003 yields a diversion rate range that is incompatible with the reported low-end value. This discrepancy introduces uncertainty in interpreting the WC74 diversion rates and raises concerns about the accuracy and reliability of the reported figures.

# 3. Prevention and Divertibility

## 3.1 Call for Service Data

Data were obtained from Computer Aided Dispatch (CAD) logs from the City of Eugene, Oregon, via a public records request. The dataset covered the period from January 1, 2016, through January 1, 2019, and included all publicly initiated calls for service handled by either CAHOOTS or the Eugene Police Department (EPD). Each record in the dataset captured details on the call type, location, dispatch status, and responding unit. Call types with fewer than 1,000 total observations were excluded, resulting in 45 call types retained for analysis.

## 3.2 Study Design and Setting

We employed a quasi-experimental Difference-in-Differences (DiD) design to estimate the causal impact of the CAHOOTS program expansion on call type rates. Conceptually, a DiD design estimates the effect of an intervention by comparing the change in outcomes over time in a group exposed to the intervention (treatment group) to the change in outcomes over time in a group not exposed to the intervention (control group). The expansion of CAHOOTS service hours offers a natural experiment that we can leverage to conduct DiD. Prior to November 1, 2016, CAHOOTS did not operate between 3:00 am and 10:00 am. The expansion occurred in two phases: 1) Partial Expansion with service added between 7:00 am and 10:00 am, effective November 1, 2016, and 2) Full Expansion with service added between 3:00 am and 7:00 am, effective January 1, 2017. While the partial expansion added some services during 7:00-10:00 am, this was a transitionary period, and CAHOOTS did not operate at full capacity until the full expansion. Our primary analysis focuses on the impact of the full expansion during the 3:00 am – 7:00 am window because this period represents the clearest pre-post condition for CAHOOTS operations, offering a distinct interval where services were entirely absent before the expansion and then fully present after. We defined the treatment group ($T_g = 1$) as calls occurring during these newly covered early morning hours (3:00 am – 7:00 am). The control group ($T_g = 0$) consisted of calls occurring during all other hours of the day (0:00 am – 2:59 am and 7:00 am – 11:59 pm). Calls were aggregated by calendar month, yielding one observation per call type, exposure group, and month.

## 3.3 DiD Model Specification

Call type-specific effects were estimated using a Negative Binomial Generalized Linear Model (GLM) to account for the count nature of the outcome variable (monthly calls) and observed overdispersion. The model specification is as follows:

$$\log\mathbb{E}[Y_{cgt}] = \beta_{0c} + \beta_{1c}T_g + \beta_{2c}P_t + \beta_{3c}Q_t + \beta_{4c}(T_g \times P_t) + \beta_{5c}(T_g \times Q_t) + \gamma_c \log \mathrm{V}_{\mathrm{gt}} + \log \mathrm{E}_{\mathrm{gt}} \quad (7)$$

In this model, $Y_{cgt}$ represents the number of calls for a specific type $c$ within an exposure group $g$ (treatment or control hours) during month $t$. The term $\beta_{0c}$ is the call type-specific intercept, indicating the baseline log rate of calls during control hours in the pre-expansion period.

The indicator $T_g$ distinguishes the treatment hours (3:00 am – 7:00 am, where $T_g$=1) from control hours (all other hours, where $T_g$=0); its coefficient $\beta_{1c}$ quantifies the "baseline gap," representing the average difference in log call rates between treatment and control groups for call type $c$ in the pre-expansion period.

To isolate the impact of the primary 3:00 am – 7:00 expansion and avoid confounding effects from the earlier, partial expansion (7:00 am – 10:00 am), our DiD specification explicitly includes terms to account for both the average effect of that initial phase and its specific differential impact within the treatment window. This ensures these effects do not bias our estimate for the full expansion.

The indicator $P_t$ identifies months within the **partial** expansion phase (November–December 2016). Its coefficient $\beta_{2c}$ captures the average change in log call rates for call type $c$ during this phase for the control group, relative to the pre-expansion period. Similarly, $Q_t$ indicates months during the full expansion phase (January 2017 onward), and its coefficient $\beta_{3c}$ reflects the average change in log call rates for call type $c$ during this period for the control group, relative to pre-expansion.

The interaction term $T_g \times P_t$, with coefficient $\beta_{4c}$, is the Difference-in-Differences (DiD) estimator for the partial expansion. It isolates the specific change in log call rates for call type $c$ within the treatment hours during the partial expansion phase, relative to the change in control hours after accounting for baseline differences.

The primary coefficient of interest is $\beta_{5c}$, corresponding to the interaction $T_g \times Q_t$. This term is the DiD estimator for the full expansion, isolating the specific change in log call rates for call type $c$ within the treatment hours during the full expansion period, relative to changes in control hours after accounting for baseline differences and partial expansion effects.

To control for variations in the overall intensity of service demand specific to each group $g$ (treatment or control hours) and month $t$, which could affect call volumes independently of the policy expansion, the model includes $\log V_{gt}$ (representing the natural logarithm of the total number of CAD calls of all types for group $g$ in month $t$). The coefficient for this term, $\gamma_c$, measures the elasticity of the expected call count with respect to this group-specific total call volume ($V_{gt}$). This means that, holding other factors constant, a 1% increase in $V_{gt}$ is associated with an approximate $\gamma_c$% change in the expected number of calls of type $c$ for that group and month.

Finally, $\log E_{gt}$ (representing the natural logarithm of total exposure hours per month for group g) is included as an offset term. This standardizes call counts into rates per hour and accounts for the differing durations of the treatment (4 hours per day) and control (20 hours per day) windows.

Overdispersion was addressed using a Negative Binomial (NB2) variance structure (Var[Y] = E[Y] + $\alpha_c$ E[Y]²). The dispersion parameter ($\alpha_c$) for each call type was estimated based on a preliminary Poisson GLM fit. To account for potential serial correlation within call types over time and group-wise heteroscedasticity, standard errors were clustered by calendar month using cluster-robust variance estimation.

## 3.4 Significance testing and multiplicity adjustment

Hypotheses regarding the DiD estimator ($\beta_{5c}$) were evaluated using two-sided tests with a significance threshold of $\alpha = 0.05$. To control the family-wise error rate arising from testing effects across 45 call types simultaneously, p-values were adjusted using the Holm procedure. A change in call rate was considered statistically significant and substantively meaningful if the Holm-adjusted p-value was less than 0.05.

## 3.5 Parallel Trends Validation

$$\log\mathbb{E}\left[Y_{cgt}\right] = \delta_{0c} + \delta_{1c}T_g + \delta_{2c}Time_t + \delta_{3c}\left(T_g \times Time_t\right) + k_c \log V_{gt} + \log E_{gt} \qquad (8)$$

The causal interpretation of our DiD estimate (β5c) depends on the assumption that treatment and control groups followed parallel trends prior to the expansion. We formally test this assumption with the model specified in Equation 7. For each call type $c$, we used only pre-expansion data ($Q_t$=0) to regress the monthly call count on the treatment indicator ($T_g$), a continuous linear time trend ($Time_t$), and their interaction term. A statistically significant coefficient on the interaction term ($\delta_{3c}$) would indicate that the trends were not parallel, violating the assumption. The null hypothesis of a zero slope (indicating parallel trends) was tested against an alternative of a non-zero slope using a significance level of $\alpha = 0.05$.

This diagnostic model was specified as a Negative Binomial regression, consistent with our main analysis. Control variables, offset, overdispersion, and clustering were handled identically to our main DiD model.

For the five call types where our primary DiD analysis yielded a statistically significant expansion effect (significant $\beta_{5c}$), we failed to reject this null hypothesis ($\delta_{3c} = 0$) in all instances, supporting the parallel trends assumption for these key findings.

However, across the broader set of call types analyzed, we found evidence suggesting a violation of the parallel trends assumption for five specific types: Assist Fire Department ($\delta_{3c} = 0.173$, p=0.0494), Unauthorized use of vehicle ($\delta_{3c} = 0.099,\ p = 0.00143$), Traffic Hazard ($\delta_{3c}$ =-0.0843, p=0.0285), Family Dispute ($\delta_{3c}$=0.21, p<0.001), and Motor Vehicle Accident ($\delta_{3c}$ =-0.0968, p=0.00764). Full test results for all call types are available in Table S7.

## 3.6 Effect-size Estimation

Following the identification of call types with statistically significant changes in volume associated with the full CAHOOTS expansion, we proceeded to quantify the magnitude of these impacts. The primary coefficient of interest, $\hat{\beta}_{5c}$, represents the estimated change in the log rate of calls. To express this as a multiplicative effect, we calculated the Incidence Rate Ratio (IRR) for each call type *c*: $IRR_c = \exp(\hat{\beta}_{5c})$.

The $IRR_c$ estimates how many times higher ($IRR_c > 1$) or lower ($IRR_c < 1$) the rate of calls of type *c* was during treatment hours in the full expansion period, compared to what would have been expected had the expansion not occurred. For instance, if calls of type *c* doubled with the CAHOOTS expansion, then $IRR_c=2$.

When a call type exhibited a statistically significant increase ($IRR_c>1$, $p<0.05$), we estimated the proportion of the observed calls during the post-expansion treatment hours that could be attributed to the CAHOOTS expansion (i.e. additional service volume beyond baseline demand, or the non-divertible fraction). This is equivalent to the Attributable Fraction among the Exposed (AFE) and was calculated for each call type as:

$$Prop_{added} = \frac{(exp(\hat{\beta}_{5c})-1)}{exp(\hat{\beta}_{5c})} = \frac{(IRR_c-1)}{IRR_c}$$

$Prop_{added}$ represents the fraction of calls of type *c* within the treatment group during the full expansion period that are estimated to be additional calls, beyond what would have been observed without the CAHOOTS expansion. The complement, $1 - Prop_{added}$, was interpreted as the divertible proportion and used for subsequent adjustments to CAHOOTS-attributable call counts.

Conversely, for call types showing a statistically significant decrease (IRRc<1, p<0.05), we interpreted this as evidence of a prevention effect, where the CAHOOTS expansion led to a reduction in calls that would have otherwise occurred. The proportion of potential calls of type *c* averted by the CAHOOTS expansion during the treatment hours, equivalent to Prevented Fraction among the Exposed (PFE), was calculated as:

$$Prop_{prevented} = 1 - exp(\hat{\beta}_{5c}) = 1 - IRR$$

$Prop_{prevented}$ estimates the fraction of calls that were *prevented* from occurring, relative to the number of calls that would have been expected in the absence of the CAHOOTS expansion during the treatment hours.

**Table S8: DiD Results**

| Call Type | DiD Coeff ($\beta_{5c}$) | p-value | Effect ($IRR_c$) |
|---|---|---|---|
| **Transport** | 2.98 | $p < 0.001$ | 18.77 |
| **Public Assist** | 2.5 | $p < 0.001$ | 11.19 |
| **Dispute** | -0.27 | $p = 0.0142$ | -0.235 |
| **Suspicious Subject** | -0.60 | $p < 0.001$ | -0.451 |
| **Assault** | -0.68 | $p = 0.00463$ | -0.493 |

Full results for all call types are available in Table S9.

## 3.7 Calculation of Adjusted Diversion Rates

Building on the DiD results, we calculated two adjusted diversion rates: the Substitution Diversion Rate (SDR) and the Prevention-Adjusted Diversion Rate (PDR). These calculations used the effect size estimates derived above and call volume data primarily from the EPD report.(*19*) The EPD report does not include combined figures for dispatched Dispute, Suspicious Subject, or Assault calls, so we source them from the CAD data.

First, we address direct diversion. The divertibility of a call type is determined by the proportion of calls within that category that would require police intervention in the absence of CAHOOTS services. For a call type *c* with a significant call volume increase following the service hour expansion, we obtain the fraction of observed post-expansion calls attributable to CAHOOTS' added service hours with $\frac{IRR_c - 1}{IRR_c}$. We interpret this share of calls above baseline as the non-divertible proportion of each call type. Call types without a significant increase corresponding to the addition of CAHOOTS services require no adjustment.

With these divertibility estimates, we recalculate the EPD's reported diversion rate. For each call type *c* with a significant proportion of calls outside the EPD scope, we adjust the raw CAHOOTS dispatch counts by multiplying by divertibility ( $1 - \frac{IRR_c - 1}{IRR_c}$ ) to recover only the baseline (police-mandate) portion.

$$AC_D = (C_{Dpa} \cdot P_{pa}) + (C_{Dtr} \cdot P_{tr}) \ + \ C_{Do}$$

$$AC_D = (5{,}788 \cdot 0.082) + (1{,}803 \cdot 0.051) \ + \ 10{,}515 = \ 11{,}082$$

$$\text{SDR} = \frac{AC_D}{D - (C_D - AC_D)} = \frac{11{,}082}{68{,}427 - (18{,}106 - 11{,}082)} = 0.18 \quad (9)$$

Here, $C$ represents the count of CAHOOTS calls, where the primary subscript D signifies the call was dispatched. The secondary subscripts denote the specific call type: pa for Public Assist, tr for Transportation, and o for all other types. $AC_D$ represents the adjusted count of dispatched calls, after multiplying the counts of specific call types by their proportional adjustment (P) $C_{Do}$ represents all other dispatched CAHOOTS call types.

We now turn to prevention. Since diversion is defined as the share of calls handled by CAHOOTS that would otherwise go to police, incorporating our prevention estimates is a natural extension. For any call types that show a statistically significant decrease in rate after expansion, we calculate the prevented proportion as (1−IRR), which represents the share of counterfactual calls that were averted by CAHOOTS. We then multiply the baseline call volume by that share to estimate the number of calls prevented.

$$PT_D = (T_{Das} \cdot P_{as}) + (T_{Dss} \cdot P_{ss}) + (T_{Ddi} \cdot P_{di})$$

$$PT_D = (1{,}652 \cdot 0.493) + (2{,}047 \cdot 0.451) + (6{,}445 \cdot 0.235) = 3{,}252$$

$$\text{PDR} = \frac{AC_D + PT_D}{D - (C_D - AC_D)} = \frac{11{,}082 + 3{,}252}{68{,}427 - (18{,}106 - 10{,}862)} = 0.233 \tag{10}$$

Here, $PT_D$ represents the number of dispatched calls prevented by CAHOOTS. $T_{Das}$, $T_{Dss,}$ and $T_{Ddi}$ represent total dispatched calls for Assault, Suspicious Subject, and Dispute, call types respectively. $P_{ct}$ indicates the proportional divertibility adjustment for each call type ct. $AC_D$ represents the sum of dispatched CAHOOTS calls after adjusting each call type based on the estimated divertible proportion from our DiD analysis. D represents the total volume of calls dispatched to either CAHOOTS or EPD. $C_D$ represents all CAHOOTS calls where a unit is dispatched. Note: Call counts for Suspicious Subject and Assault were not available in the EPD report so we derived them from the CAD data. All other values were extracted from the EPD report.

# 4. Diversions Of Overlapping Mandate

## 4.1 Determination of Calls within the overlapping mandate

We must establish clear criteria to identify which calls are within the "overlapping mandate," that is, which calls could be answered by either EPD or CAHOOTS. Ideally, for the purpose of our analysis, dispatch systems would explicitly flag which emergency response agencies could possibly address each call (as seen in the emergency response system in Denver. Unfortunately, this approach to data collection is not widespread, and specifically not in use in Eugene. Recognizing that many municipalities share this same data limitation, we developed an empirical approach to estimate if a call type is within the overlapping mandate based on observed response patterns. Call type response patterns are not a perfect proxy for per-call eligibility in that 1) they fail to account for variance in per-call agency eligibility within a call type, and 2) they are sensitive to biases in which agency is actually dispatched, which may be influenced by non-eligibility factors like unit availability.  For these reasons, our approach here should be considered a rough approximate first effort with available data.

We define the response parity threshold as the maximum percentage of a given call type that can be handled by a single agency while still falling under the overlapping mandate. For instance, setting this response parity threshold to 0.90 means a call type is included only if neither agency handles more than 90% of calls; implicitly, this means that neither agency answers fewer than 10% of calls. At the strictest response parity threshold of 0.5, only call types handled equally by both agencies would be included in the overlapping mandate. To compute the Overlapping Mandate Diversion Rate (OMDR) we divide the total number of CAHOOTS calls in included call types by the total number of calls in those same call types.

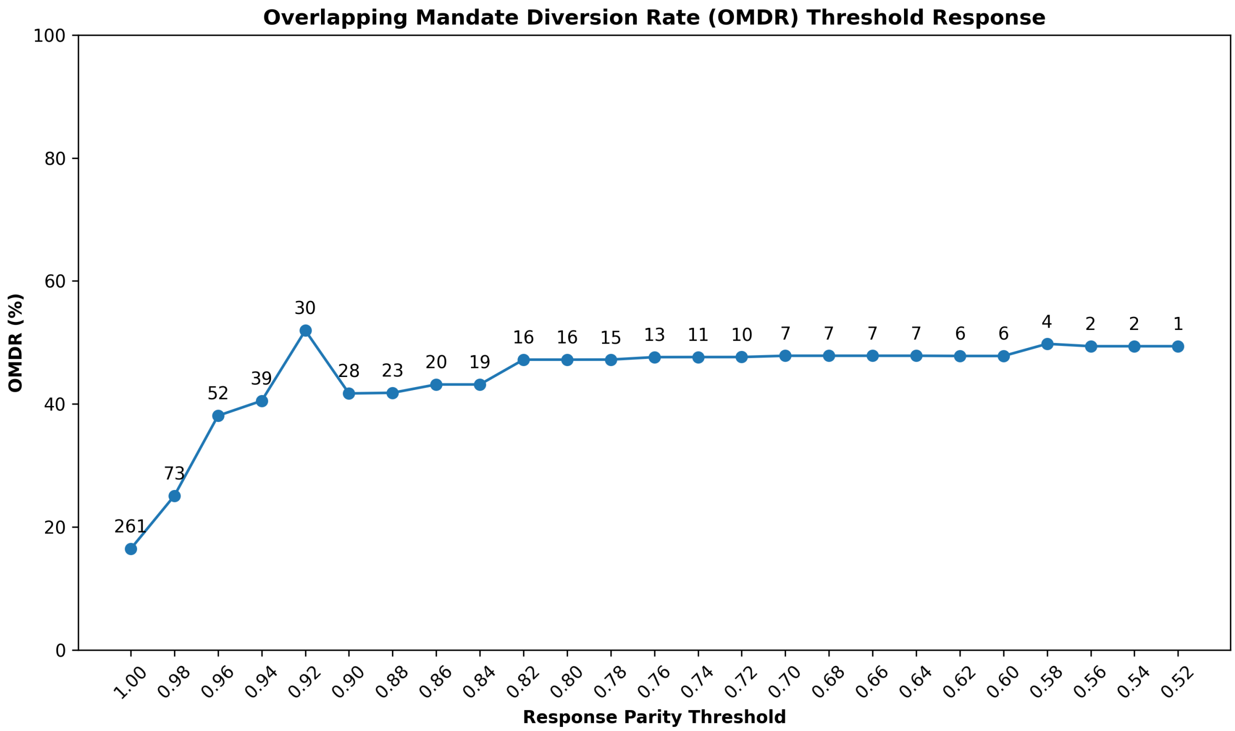


**Figure S1.** Overlapping Mandate Diversion Rate vs. Response Parity Threshold. The x-axis shows the response parity threshold, ranging from 1.00 (all call types) down to 0.50 (only equally shared call types). The y-axis shows the calculated OMDR. The numbers above each point indicate how many call types are included at each response parity threshold.

With the most permissive end response parity threshold (1.00, including all call types), the diversion rate is equivalent to the naïve computation of all CAHOOTS calls divided by the total number of calls (Figure S1). As the threshold becomes more restrictive, the OMDR initially fluctuates as high-volume, low-overlap call types (predominantly handled by EPD) are excluded. For example, CAHOOTS was dispatched to 69 calls involving theft, whereas the EPD dispatched to 10,933. As the call types with imbalanced agency response are excluded, the OMDR stabilizes between 42% and 50% for thresholds ranging from 0.92 to 0.52, representing 1-30 call types.

For downstream calculations in this analysis, we consider a response parity threshold of 0.85. We chose this threshold because of the stability of OMDR for thresholds from .92 to .52.