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Abstract

This paper studies temporal factors influencing the effectiveness of don't drive appeals (DDAs) which policy-makers use to encourage motorists to voluntarily reduce driving during transitory high pollution episodes. We derive and empirically validate a theoretical framework for DDAs where the desired behavioral response is sensitive to the number of consecutive DDA days and recovery time between episodes. Our analysis of daily traffic flows from automatic traffic counters in Stuttgart, Germany shows that DDAs at best reduce overall car trip demand during pollution events by less than 1% on average, but treatment effects vary. Difference-in-difference event study estimates reveal that DDAs: i) lead to approximately 3% traffic reductions on the first three days of DDAs and taper off in effectiveness during longer episodes, ii) regain effectiveness at the tail end of DDA episodes once local authorities announce when they will be lifted, and iii) only reduce city center traffic following lengthy recovery periods between events. Our findings provide evidence that temporal factors like social norms and intertemporal substitution dynamically affect voluntary short-term pollution mitigation programs. They also confirm prior North American evidence on DDA traffic displacement and limited overall impact in a European setting.

Keywords: pollution mitigation, information-based regulation; voluntary policies; air quality alerts; policy timing; prosocial behavior; transportation choice

JEL Classification: D91, Q52, Q53, R40

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1 Introduction

Policy-makers in urban areas commonly use air quality alerts (AQAs) to inform the public of heightened ambient air pollution levels and to appeal for short-term adaptation and mitigation. Individuals, particularly those from at-risk populations, try to reduce pollution exposure during AQAs by rescheduling commutes (Saberian et al., 2017), abstaining from strenuous outdoor activity (Fan, 2024; Ward and Beatty, 2015), forgoing leisure in outdoor recreational spaces (Janke, 2014; Graff Zivin and Neidell, 2009), and investing in protective face masks (Liu et al., 2017), but responsiveness diminishes on consecutive alert days (Graff Zivin and Neidell, 2009; Saberian et al., 2017).[1] Previous evidence on voluntary pollution mitigation during AQAs is less conclusive, and its temporal dimension remains understudied. North American programs that combine AQAs with don't drive appeals (DDAs) find that DDAs are often ineffective in reducing car use (Noonan, 2014; Sexton, 2012; Cummings and Walker, 2000), while Caplan (2023) and Tribby et al. (2013) show they may even inadvertently increase driving. Cutter and Neidell (2009) are the only ones to document an effective DDA. In this paper, we examine whether time-related DDA design choices, namely event duration and between-event recovery time, affect whether commuters voluntarily drive less during DDAs by studying a policy setting where they are implemented frequently and often for extended periods.

We begin by drawing from existing modal switching models (Cutter and Neidell, 2009; Sexton, 2012; Basso and Silva, 2014) to introduce a theoretical framework for DDAs that predicts driving reductions and incorporates dynamic social norm effects. Despite evidence of shortcomings in other contexts (Noonan, 2014; Sexton, 2012; Cummings and Walker, 2000),[2] policy-makers continue to rationalize the use of moral appeals (Ito et al., 2018; Ferraro et al., 2011; Cutter and Neidell, 2009; Reiss and White, 2008) for voluntary driving reductions, for example, as part of Action Day programs in US cities[3]

[1] This is called alert fatigue in the literature. Graff Zivin and Neidell (2009) and Saberian et al. (2017) study multi-day AQAs and find evidence for alert fatigue after the first AQA day.

[2] These findings correspond with first-order expectations under the assumption of self-interested, utility-maximizing agents. Motorists, who pollute the air and thereby impose a negative externality on others, optimize their private well-being (including private health costs) when deciding how much to drive but do not factor in the social cost of their choices. In aggregate, this leads to a socially-inefficient pollution surplus. Policy-makers attempt to solve this collective action problem using moral levers (i.e. DDAs) or congestion management policies (i.e. transit fare subsidies, congestion pricing, vehicle bans, etc.) to make driving relatively more costly and shift individual driving choices towards the socially-optimal level. However, we would not expect self-interested, utility-maximizing agents to be swayed by an appeal for collective benefits at a private cost, beyond its direct effect on private well-being.

[3] See `https://www.airnow.gov/aqi/action-days/`(retrieved June 29, 2023) for a list of Action Day programs in the US.

and similar policies in major urban areas around the world.[4] Our first contribution in this paper is to model this thinking.

We then test this model empirically in Stuttgart, Germany, a European metropolitan setting seemingly well-suited for a program targeting voluntary driving reductions due to its abundant transit alternatives[5] and widespread environmental preferences.[6] Local authorities in Stuttgart, Germany raised a particulate matter AQA (*Feinstaubalarm*) to inform the public of high ambient air pollution levels during multi-day periods with limited atmospheric interchange capacity from January 2016 to April 2020[7]. When Stuttgart's AQA is active, authorities also temporarily reduced public transit fares and widely broadcast DDAs encouraging motorists to stop driving cars and to switch to riding public transit, cycling, walking, working from home, or otherwise abstaining from driving. Our ordinary least squares (OLS) regression analysis leverages daily traffic flows from 56 automatic traffic counters (ATCs) located within and just beyond the Stuttgart administrative border to measure the impact of DDAs on aggregate car trip demand. Our preferred estimation framework studies multi-day, dynamic DDA effects using a difference-in-difference (DiD) event study design that compares traffic levels in Stuttgart with traffic levels in the neighboring metropolitan city of Munich using data from an additional twenty ATCs located there.[8]

Our empirical results make three additional contributions to the literature. First, we study the overall impact of DDAs on voluntary driving reductions outside the United States for the first time, and thereby provide evidence about whether previous results transfer to other policy settings. Our analysis of Stuttgart traffic data shows that vehicle flows in the city decrease at best by about 0.6% on days when authorities implement

[4] For example, see program descriptions for Korea (`https://airkorea.or.kr/eng/O3Alert?pMENU_NO=162`, retrieved December 2, 2024) or Île de France, France (`https://www.airparif.fr/en/index.php/procedure-dinformation-et-dalerte`, retrieved December 2, 2024).

[5] Stuttgart has an extensive public transportation network consisting of seventeen regional train lines, seven suburban train lines, nineteen light-rail lines, and 390 bus lines.

[6] A coalition led by the Green party has governed the state of Baden-Württemberg since 2011, Germany's first Green party state Minister-President was elected in Baden-Württemberg in 2011 and reelected in 2016 and 2021, and a Green party politician has held office as Stuttgart's Mayor since 2013.

[7] The German Weather Agency (Deutscher Wetterdienst, *DWD*) defines days with a limited interchange capacity as days with low rainfall, low wind speed, nighttime ground inversions, and low daytime atmospheric mixing layers. In these conditions, particulate matter pollution can easily accumulate to higher levels. The program targeted collective environmental benefits from emissions reductions related to to driving reductions. See Background for more details.

[8] Munich is a similarly sized metropolitan city in southern Germany (metropolitan region population: 6.2 million in Munich vs. 5.3 million in Stuttgart in 2023) with highly correlated traffic, pollution, and meteorological conditions that, like Stuttgart, failed to comply with EU air quality regulations during the DDA policy implementation period (2016-2020) but, unlike Stuttgart, did not implement an AQA program or a DDA policy.

DDAs. Previous evidence on DDA effectiveness finds that DDAs can be moderately effective (up to a 3% reduction, Cutter and Neidell, 2009), statistically ineffective (Noonan, 2014; Sexton, 2012; Henry and Gordon, 2003; Cummings and Walker, 2000), or even counter-productive (Tribby et al., 2013) in temporarily abating driving in the United States. Unlike most previously studied programs in North America, our empirical setting has an abundance of transit alternatives and widespread environmental preferences, suggesting that a DDA has high impact potential. However, estimated DDA impacts in our metropolitan European setting appear no more effective than previously studied DDA programs in the North American context.

Second, we highlight temporal heterogeneity in DDA effectiveness. We show that DDAs in our setting lead to traffic reductions up to 3% on the first three DDA days after activation, but that effectiveness wanes during prolonged DDAs. Unlike previous studies that are limited to analyzing second day alert fatigue (Graff Zivin and Neidell, 2009; Sexton, 2012; Saberian et al., 2017), our empirical setting enables us to evaluate alert effectiveness over a much longer treatment period. We find evidence suggesting that DDAs are, in general, most effective when they are soon to be lifted and that traffic may rebound on the second day after DDAs end, which both point to intertemporal substitution factoring into decisions about when to adhere to appeals for voluntary pollution mitigation. In general, our results on prolonged DDA treatment exposure may be particular valuable in settings with more persistent pollution episodes than previously studied North American settings.

Third, we provide novel evidence about the sensitivity of DDA effectiveness to the recovery period between DDA events. In our theoretical framework, we hypothesize that DDAs are less effective after short recovery periods. Our empirical results confirm this prediction and show that DDAs implemented with at least a nine day recovery period reduce traffic by nearly 5% at the city center. To the best of our knowledge, this paper is the first to test the importance of this temporal dimension for DDAs empirically and provides guidance for policy-makers deciding how to incorporate frequency considerations into the design of AQAs, DDAs, and other voluntary mitigation policies.

The remainder of this paper is structured in the following manner. The next section provides background information about Stuttgart's AQA program and its accompanying DDA. In section 3, we formalize a theoretical framework for DDAs. Section 4 describes the data we use for our empirical analysis, while section 5 explains our estimation strategy for identifying DDA impacts. Section 6 discusses our results and section 7 concludes.

2 Background

2.1 Stuttgart's Air Quality Alert Program

On January 1, 2016, Stuttgart city officials introduced its AQA program as part of a multi-policy air quality plan targeting compliance with EU air quality standards.[9] During the PM season,[10] the AQA program notified residents in the greater Stuttgart metropolitan region of upcoming and ongoing poor air quality episodes via electronic road signs, radio, television, social media, and newspapers. The AQA program's DDA encouraged motorists not to drive and instead to use less-polluting transportation. In contrast to health-oriented air quality alert programs in other cities, local authorities did not explicitly warn Stuttgart residents about the negative health effects of air pollution exposure; the AQA program focused on the collective environmental benefits or so-called "quality-of-life improvements" that could result from a widespread temporary switch away from cars.[11] In early 2020, local authorities announced plans to abandon the AQA program after April of that year, citing its success in reducing air pollution in the city.[12]

The city of Stuttgart has approximately 630,000 residents, and based on commuting statistics from the German Federal Employment Agency and the Baden-Württemberg State Statistical Office, we estimate that roughly 382,000 commuters (73% of individuals employed in the city) travel by car or motorcycle in the city of Stuttgart on a given workday, compared to 66,000 (13%) who take public transit and 75,000 who walk or bike (14%).[13] In two telephone surveys conducted by the city government in early

[9]Under EU Air Quality Directive 2008/50/EC, daily average ambient PM_{10} concentrations are not to exceed 50 $\mu\ g/m^3$ more than 35 times per calendar year. From 2004 through 2017, daily ambient PM_{10} concentrations at the Neckartor air quality monitor in central Stuttgart annually exceeded this legal threshold. The city government, under the auspices of the state government, implemented an air quality improvement plan which included establishing a low emissions zone and corresponding bans on high polluting vehicles, upgrading public transit and bicycle infrastructure, investing in cleaner public transit fleets, expanding park-and-ride parking lots, lowering speed limits on busy streets, banning wood burning stoves during AQAs, reducing public transit fees, increasing street cleaning, and incentivizing employers to recruit employees to purchase monthly public transit tickets.

[10]Stuttgart authorities can call an AQA during the particulate matter (PM) season from October 15th to April 15th, when PM levels are typically highest.

[11]Residents may certainly have been aware of air pollution exposure's negative health impacts *ex ante*, may have become informed of them through AQA-adjacent media programming, or may have inferred them from the nature and language of the AQA program.

[12]*Stuttgarter Zeitung.* 2020. Bessere Luft in Stuttgart: Feinstaubalarm wird im April abgeschafft. January 17, 2020.

[13]Hence, for each percentage point change in daily car commuters on DDA days, we estimate that about 4,000 car commuters switch their mode of transit or work from home. We anticipate that these are low ballpark estimates for the daily number of vehicles on Stuttgart roads, as our calculations do not include non-employed motorists (e.g. retirees, students, unemployed people, etc.), nor do estimates

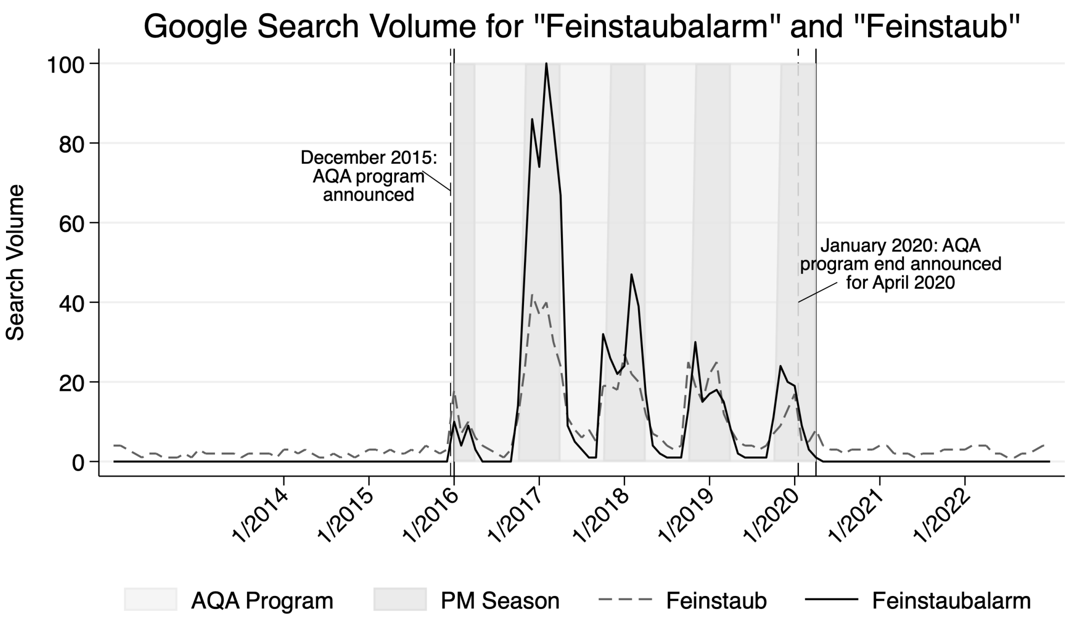

Figure 1: Online search interest for particulate matter alert ("*Feinstaubalarm*") and particulate matter ("*Feinstaub*", PM) in Baden-Württemberg from January 2014 through May 2022. From January 2016 to April 2020, the AQA program was active annually during the PM season from October 15 to April 15. Search volume is relative to maximum search volume (=100) in February 2017. Data source: Google Trends.

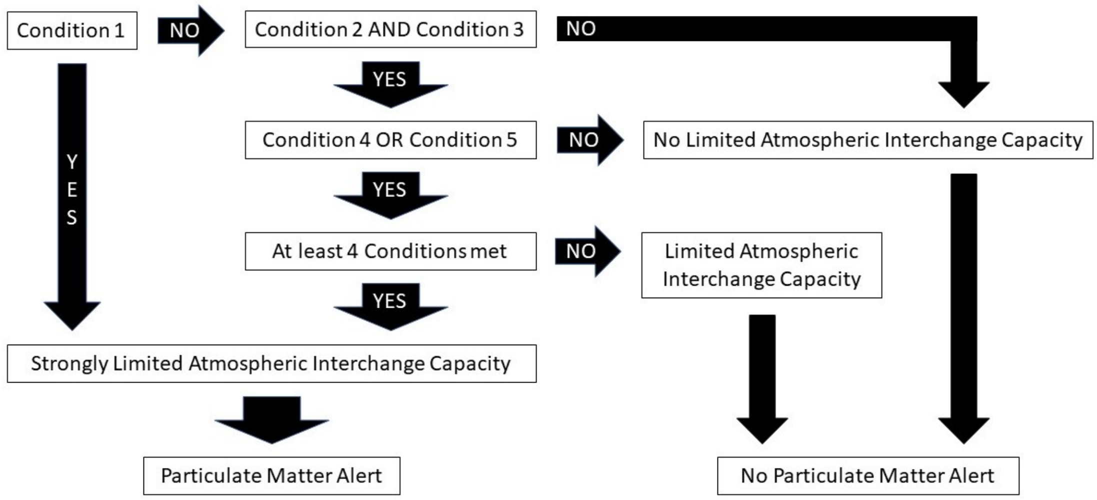

Figure 2: DWD Decision Tree for calling and ending an AQA. The "Particulate Matter Alert" outcome leads authorities to broadcast a Don't Drive Appeal (DDA). Information Source: DWD.

2016, 90-92% of respondents (n_1=1,008, n_2=1,004) reported having heard about the AQA program and 15-25% of respondents stated that they reduced their car use on DDA days.[14] The survey results and online search query data (figure 1) confirm that AQA messaging arrives in the general population. However, survey responses were self-reported and were collected when the AQA program was new. Surveyors neither elicited nor observed the actual extent of driving reductions, and social-desirability bias presumably leads individuals to over-report driving reductions, so these findings must be interpreted cautiously.

2.2 Don't Drive Appeal Conditions and Timing

Stuttgart authorities decide whether to call an AQA and broadcast a DDA using a decision tree based on six binary atmospheric conditions. On each day during the PM

include other reasons for driving into the city (e.g. leisure or business travel, through traffic, etc.).

[14]See *Befragung zum Thema Feinstaubalarm in Stuttgart und Umgebung* (URL: `https://vm.baden-wuerttemberg.de/fileadmin/redaktion/m-mvi/intern/Dateien/PDF/Feinstaub-Alarm_Auswertung_Umfrage__160208.pdf`, published: February 8, 2016, retrieved: December 2, 2024) and *Befragung zum Thema Feinstaubalarm in Stuttgart und Umgebung im Zeitraum 26.02.2016 bis 28.02.201* (URL: `https://vm.baden-wuerttemberg.de/fileadmin/redaktion/m-mvi/intern/Dateien/PDF/Feinstaub-Alarm_Auswertung_Umfrage__160208.pdf`, published: March 10, 2016, retrieved December 2, 2024).

season, the German Weather Agency (DWD) takes stock of the following conditions:[15]

- Condition 1 (primary): Whether the daily mean PM_{10} concentration at Neckartor monitoring station is over 30 μg/m^3 and no rainfall is forecast until 12am of the first forecast day.[16]
- Condition 2: Whether no rainfall is forecast for both the bridge day[17] and the first forecast day.
- Condition 3: Whether wind blows with an average wind speed over 3 km per hour from 180°-330°.
- Condition 4: Whether there is a nighttime ground inversion.[18]
- Condition 5: Whether there is a low daytime mixing layer.[19]
- Condition 6: Whether average wind speed is below 3 km per hour.

According to the outcome of each binary condition and the corresponding decision rules in figure 2, DWD classifies the atmospheric interchange capacity as either "not limited," "limited" or "strongly limited" with only the latter leading to an AQA. There are two paths to an AQA. First, as the primary condition, fulfilling condition 1 is sufficient for activation. Second, if condition 1 is not satisfied, then conditions 2 and 3, either condition 4 or 5, and at least four criteria overall must be fulfilled for the city to call an AQA. In the latter path, the 30 μg/m^3 threshold from condition 1 is no longer relevant for activation.

If local authorities decide to call an AQA, they begin notifying the public in the early afternoon of the issue day of high air pollution levels and about a forthcoming DDA that will be activated 36 hours later (see figure 3, event time: -2). A bridge day (event time: -1), when the public continues to be informed about the upcoming AQA but the DDA has not gone into effect, follows the issue day. The DDA comes into effect after the bridge day at 0:00 am of the first forecast day (event time: 0). The DDA continues for at least a second day (event time: 1) and remains in effect until the

[15] See *Schadstoffrelevante Kriterien des Deutschen Wetterdienstes* (URL: `https://www.stuttgart.de/medien/ibs/Neue-DWD-Kriterien-300916.pdf`, retrieved: December 2, 2024)

[16] Snowfall and sleet are treated as rainless.

[17] There is a one day pause between the day an AQA event is announced and the day the DDA is activated.

[18] Nighttime ground inversion is defined as an air layer within which temperature increases with altitude. Such an inversion traps particulate matter in the Stuttgart valley.

[19] The mixing layer height indicates the interchange capacity of the low lying air masses. The lower the mixing layer height, the smaller is the interchange capacity. The criterion is fulfilled if the mixing layer height is lower than 500 meters during the day.

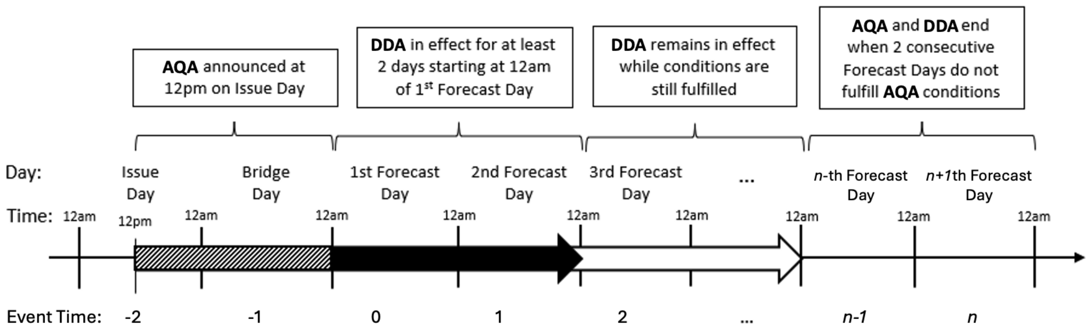

Figure 3: Air quality alert (AQA) and don't drive appeal (DDA) timing. For our analysis, DDA activation corresponds with event time period 0. Information Source: City of Stuttgart.

DWD forecasts two consecutive days where the atmospheric interchange capacity is not "strongly limited." Local authorities announce the end of the AQA and DDA two days before DDA messaging subsides.

Importantly, AQA and DDA designation is based on weather forecasts, not *actual* weather conditions on a given day. If authorities call an AQA, unanticipated meteorological changes between the issue day and any subsequent day may improve atmospheric interchange capacity to the extent that some AQA conditions may no longer be fulfilled on that day. On these days, DDA messaging continues to be broadcast although the atmospheric conditions are not necessarily fulfilled. By similar logic, actual meteorological conditions may worsen the atmospheric interchange capacity to the extent that, on a given non-DDA day, a DDA should have been broadcast, even though it was not. At the margin, local authorities can exercise limited discretion when deciding whether to initiate an AQA event and broadcast the DDA, specifically in cases when thresholds are just barely met (e.g. a small amount of rainfall may not be deemed sufficient to clear particulates from the air).

3 Theoretical considerations

Stuttgart's policy-makers employ a DDA in the ostensible belief, publicly expressed, that a morally framed request directed at car owners, combined with a public transit subsidy, will reduce driving. To see whether this belief can be rationalized, we develop a plausible mental model that formalizes this thinking. This simple theoretical framework is informed by existing models of modal switching for the *Spare The Air* (STA) program in the San Francisco, USA Bay Area (Cutter and Neidell, 2009; Sexton, 2012) and urban congestion management policies in London, UK and Santiago, Chile (Basso and Silva, 2014). To adapt the framework for the case at hand, we explicitly downplay the individual health aspects at the heart of the Bay Area's STA program, which – unlike for the case of Utah's "yellow alert days" (Caplan, 2023) – are not part of Stuttgart's DDA. We instead emphasize its moral appeal considerations.

The literature identifies injunctive and descriptive norms as the main pathways through which a moral appeal can change the behavioral calculus of which action to choose (Bicchieri, 2005). Injunctive norms define how an individual ought to act. They constitute abstract moral absolutes, that is behavioral benchmarks independent of other people's behavior. Descriptive norms, on the other hand, reflect how most other people act. They are observable behavioral patterns in the population. In both cases, the literature has argued, individuals receive emotional rewards or losses from themselves and others as a function of adherence to or deviation from the norm. The associated feelings of righteousness and approval and of shame and guilt enter the utility function and can thus affect decision-making (Battigalli and Dufwenberg, 2007; Zafar, 2011).

Policy-makers are unlikely to be unaware of the subtle distinction between injunctive and descriptive norms. Yet, their mental model of DDAs may well capture the idea of injunctive norms by postulating that a DDA makes people attach positive feelings to deciding not to drive.[20] Descriptive norms could be captured by attaching to driving a negative feeling whose strength depends on the effectiveness of the appeal on others: Guilt and shame are strongest if the individual driver finds himself the only driver on the road, particularly if watched by non-drivers. They do not arise when traffic density during the DDA event is the same (or even higher) than before (Zafar, 2011). Considerations of positive and negative feelings triggered by adhering and deviating from norms would provide policy-makers with a behaviorally informed model of how car owners respond to the introduction of a DDA. They can also be extended to the question of how effective a DDA is likely to be over time. Policy-makers' intuition that the impact of DDAs wears off over a multi-day DDA event and needs time to recover between DDA events accords with well-established findings in psychology. Experimental tests of the theory of "ego depletion of self control" (Baumeister et al., 2000) consistently show that the emotional costs of not complying with norms that require a change from previous behavior decrease over time (Dang, 2018) and require a 'recovery period' between norm activation events (Tice et al., 2007). Considerations of both a static and dynamic nature

[20] Equivalently, it could be introduced as a negative feeling attached to driving. Analytically, it leads to the same results.

are therefore likely to populate policy-makers' mental models of how a DDA affects driving.

3.1 Static model

To give some analytical heft to policy-makers' reasoning, we assume in line with the static congestion model of Basso and Silva (2014) that at any given point in time t, each individual i with access to a car and wishing to travel decides between driving (D) and not driving (ND) to reach their destination.[21] Driving is associated with utility (time arguments suppressed)

$$U_i^D = V_i^D - \tau_i t^D (1 + Q^D) - p^D - \mathbb{1}_A E_i \max\left\{(\overline{Q}^D - Q^D); 0\right\} \tag{1}$$

while not driving is associated with utility

$$U_i^{ND} = V_i^{ND} - \tau_i t^{ND} - p^{ND}(1 - \mathbb{1}_A \delta) + \mathbb{1}_A G \tag{2}$$

with $\mathbb{1}_A$ an indicator variable that is one if an appeal has been issued and zero otherwise.

Expressions (1) and (2) capture that in the absence of a DDA ($\mathbb{1}_A = 0$), the respective utilities are a function of the intrinsic value that individual i associates with driving D and not driving ND, V_i^D and V_i^{ND}, the expenses of driving and not driving at market prices, p^D and p^{ND}, and the mode-independent[22] opportunity cost of time τ_i multiplied by the mode-specific travel time, t^D and t^{ND}. As in other models, total driving time is approximated as linear in car traffic density, measured by the aggregate demand for driving Q^D, along the entire itinerary, $t^D(1 + Q^D)$.[23] The driving-related air quality impacts that play a central role in the health-messaging models by Cutter and Neidell (2009) and Sexton (2012) are neglected in our representation of the policy-makers' mental model of moral appeals.

When a DDA is issued ($\mathbb{1}_A = 1$), three additional factors in expressions (1) and (2) are activated. First, in (2), the policy-maker reduces the cost of public transit through a discount δ, reducing non-driving expenses to $p^{ND}(1 - \delta)$. Second, also in (2), the policy-

[21] These model formulations purposefully neglect the extensive margin of deciding not to travel.

[22] Empirical evidence points to mode dependence: Time spent in one's own car has a lower opportunity cost than time spent in public transit. We abstract from this detail here.

[23] Total travel time is t^D when no other car is on the road ($Q^D = 0$) and increases in proportion to use by drivers. The linear approximation overestimates the effect of density on travel time for low levels of density and vice versa for high levels. This will lead to a slight overestimation of the effect of a DDA close to road capacity.

maker conveys through the appeal an injunctive norm that foregoing the use of car is the 'right thing to do'. The affective benefits of not driving are captured by a warm glow parameter G associated with norm compliance. Third, in (1), the DDA conveys a descriptive norm about driving: The greater the reduction in traffic densities during the DDA event relative to before, the greater the emotional cost to someone still driving. To approximate this effect, a simple linear formulation captures the emotional costs associated with violating the descriptive norm by driving as $E_i \max\left\{\overline{Q}^D - Q^D; 0\right\}$, with $\overline{Q}^D$ denoting aggregate demand for driving outside a DDA event. For traffic densities Q^D at or above pre-DDA levels, the emotional cost of driving is zero; for densities below, it is $E_i(\overline{Q}^D - Q^D)$. To bound the possible magnitude of the emotional cost, we assume for simplicity that $E < \tau t^D$, i.e. the marginal driver contributes more to road congestion than to relieving emotional cost.

As in Basso and Silva (2014), equilibrium traffic is the aggregate outcome of individuals deciding to drive if $U_i^D - U_i^{ND} > 0$. Across individuals, this leads to aggregate demand for driving of

$$Q^D = \sum_i \mathbb{1}_i^D, \tag{3}$$

with $\mathbb{1}_i^D$ and indicator variable that is one if for individual i, $U_i^D - U_i^{ND} > 0$.

As a result of the congestibility of the road network, there is a demand equilibrium outside DDA events with a simple closed-form solution under the assumption of identical agents of the type

$$\overline{Q}^D = \frac{1}{\tau t^D}\left\{\Delta V - \Delta p - \tau \Delta t\right\} \tag{4}$$

with $\Delta V = V^D - V^{ND}$ denoting the difference in intrinsic values, $\Delta p = p^D - p^{ND}$ the difference in expenses, and $\Delta t = t^D - t^{ND}$ the difference in travel time between driving and not driving. Equilibrium traffic density increases in the intrinsic value differential and decreases in the price and travel time differential between driving and not driving. It is scaled down by the effective cost of time of driving τt^D on account of the congestion externality that every driver imposes on all other drivers in the road network.

A few steps of simple algebraic manipulation also yield the equilibrium traffic density during a DDA as

$$Q^D = \overline{Q}^D - \frac{G + p^{ND}\delta}{\tau t^D - E} \tag{5}$$

This leads to our first hypothesis.

Hypothesis 1 *A DDA reduces equilibrium traffic: Static equilibrium traffic density is* *always lower in the presence of a DDA compared to its absence. The reduction in equilibrium traffic depends positively on the level of material incentives for modal switch and on the warm glow of norm-compliant behavior.*

Hypothesis 1 predicts that the first-order impact of a DDA is to reduce traffic. This means that the policy maker achieves the intended policy impact of the DDA in equilibrium. The reduction increases in the warm glow of the appeal, G, and in the public transit discount, δ. Their effect size is scaled by the effective cost of driving time, τt^D, net of the emotional cost of driving when others do not, E. The static congestion model highlights the presence of an instrument for inducing a switch from driving that policy-makers in the city of Stuttgart did not consider: Increasing travel time t^D through speed restrictions.

3.2 Dynamic considerations

On most days of the year, potential drivers take their driving decision against the background of no DDA, consistent with a predicted density $\overline{Q}^D$. The announcement of a DDA, its implementation for an uncertain length of time, the announcement of its removal, and the removal represent four transitions during which traffic density is driven by additional dynamic factors. At least two factors are at play that shape changes in traffic densities during transitional periods, intertemporal substitutability and "ego depletion".

The literature commonly assumes that households aim to realize an individually optimal pattern of driving and non-driving that is determined by finite intertemporal substitutability between driving today and driving tomorrow (Cutter and Neidell, 2009; Rivera, 2021; Caplan, 2023).[24] Deviations from this pattern are costly in welfare terms, yet reflect optimal adjustments to a DDA shock. Depending on whether the DDA shock is in the form of a DDA being announced to be coming into force or to be lifted,

[24]Theory does not provide a complete characterization of individual optimal dynamic demand behavior for a congestible setting in which a third party (in this case the policy-maker) changes the cost structure of consumers in a stochastic way. There is a literature on optimal dynamic behavior in settings such as air travel in which parties on the supply side, such as airlines, have committed to supplying a certain capacity at a certain point in time, but have not committed to a price path up to that time (Deneckere and Peck, 2012; Board and Skrzypacz, 2016; Dilme and Li, 2019). Another related literature examines labor-leisure choices in stochastic decision environments (Camerer et al., 1997; Hoffmann and Rud, 2024). While related, neither of these approaches accurately captures the specifics of a modal transport choice of a private household facing the probabilistic imposition and lifting of a DDA. In the appendix, Caplan (2023) provides a possible theoretical model based on the behavior of myopic individuals. Such models make somewhat different predictions than those based on dynamically optimizing individuals (e.g. Dilme and Li, 2019).

this adjustment can have two effects. In the first case, there is a potential anticipation effect: Some household now bring forward to the bridge day driving activities that would otherwise has happened on a day that now falls into the DDA episode. This gives rise to Hypothesis 2.

Hypothesis 2 *There is an anticipation effect of announcing a DDA such that traffic is higher on bridge days. Households' planning horizons allow a share of driving activities to be shifted from a future DDA day to the bridge day so as to benefit from a higher net utility of driving on a non-DDA day.*

We expect the anticipation effect on traffic to be positive, but limited since the DDA announcement only allows for a single bridge day before the DDA comes into force.

In the second case, the announcement of the DDA being lifted, there is a potential postponement effect: Some households that would have driven on a DDA day now shift driving activities backwards. This allows them to benefit from the higher intrinsic utility of driving on a non-DDA day tomorrow rather than driving on a DDA day today. The presence of a postponement effect affects traffic volumes both on the day ending the DDA and on the first non-DDA day.

Hypothesis 3 *There is a postponement effect of lifting a DDA such that traffic is lower on the n-th day of a DDA if that day precedes the lifting of the DDA – and higher on a non-DDA day if that day is the first day following a DDA. Households' planning horizons allow a share of driving activities to be shifted from a current DDA day to the following non-DDA day so as to benefit from a higher net utility of driving on a non-DDA day.*

Hypotheses 2 and 3 summarize our predictions of change in traffic during the transition from a non-DDA to a DDA phase and vice versa, driven by intertemporal substitution once the uncertainty of whether a transition will take place has been resolved. Hypothesis 4 completes the analysis with a focus on the dynamics during the DDA.

For the period during which the DDA is in force and its lifting has not been announced yet, expression 5 provides a simple characterization. This characterization suggests a constant level of traffic unless there are changes in the emotional cost of non-compliance with the DDA norm (E).[25] Such changes are consistent with empirical evidence that supports theories of "ego depletion". This depletion process leads to an emotional cost

[25] Additional factors could be changes either in the policy variable δ or in the psychological variables of warm glow (G). For the first, there is no corresponding data in our empirical context. For the second, we are not aware of established theories of the dynamics of warm glow.

of driving (E) that is highest on the first day of a multi-day DDA event and declines over the duration of the DDA, leading to an increase in traffic.[26]

Hypothesis 4 *There is an ego depletion effect of a continuing DDA such that traffic increases during a multi-day DDA towards non-DDA levels until the lifting of the DDA is announced.*

A corollary of Hypothesis 4 is that – since ego depletion requires a recovery time – drivers are predicted to be less responsive to a DDA after shorter recovery periods between DDA events.

Together, hypothesese 1 through 4 emphasize three aspects. One is that policy-makers can rationalize their belief in the effectiveness of DDAs: Invoking the norm-setting effects of DDAs in a behaviorally informed model provides a causal mechanism for affecting the choice whether to drive or not. The second is that the predicted equilibrium car traffic density under a DDA is below non-DDA levels. The third aspect is that the dynamic patterns of driving choices within and between multi-day DDA events make specific empirical predictions: Following the announcement of a DDA, traffic volumes first increase on the bridge day due to an anticipation effect before dropping on the first DDA day. Traffic then recovers through ego depletion, before the postponement effect induces a drop on the last DDA day and a surge of traffic on the first non-DDA day. The reduction in traffic due to the DDA is expected to be negatively affected when DDA events are spaced closely together.

While the framework is good at capturing the moral appeal considerations of policy-makers, it probably does injustice to their understanding of the complexity of driving decisions. For example, it neglects issues of expectations and learning that are likely to be particularly important during early phases of the DDA program as car owners closely observe traffic densities. It also neglects health-related aspects of driving decisions (Cutter and Neidell, 2009; Sexton, 2012) and the congestibility of public transit (Basso and Silva, 2014). These complexities can be expected to impact on the success of DDAs – and to be part of the ex-ante assessment undertaken by policy-makers in a more or less systematic fashion.

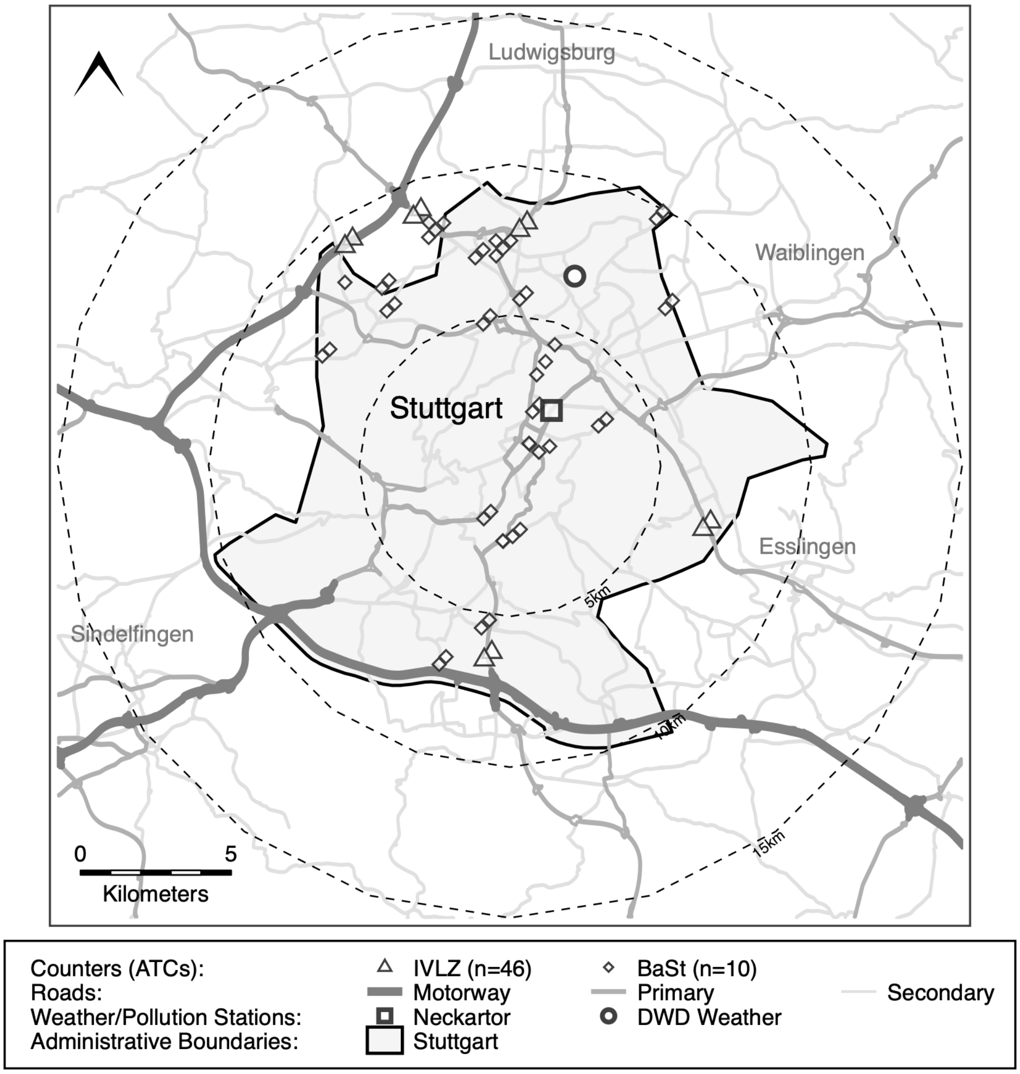

Figure 4: Stuttgart with automatic traffic counters (ATCs) by data source, road network, Schnarrenberg DWD weather station, and Neckartor AQA trigger monitor. Data sources: OpenStreetMap, IVLZ, BaSt, BKG, LUBW, and DWD.

Table 1: Summary Statistics: Vehicles per Day by City and Day-of-the-Week

	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Overall
Stuttgart, n=56								
Mean	18,889.0	19,232	19,743.7	20,142.8	20,119.7	16,156.6	13,274.3	18,238.0
Std. Dev.	14,879.6	15,229	15,469.0	15,709.0	15,862.4	12,840.2	11,191.5	14,745.2
Obs.	3,992.0	3,982	3,949.0	3,954.0	3,953.0	3,975.0	3,868.0	27,673.0
Min	37.0	56	51.0	75.0	47.0	59.0	17.0	17.0
Max	66,072.0	67,423	69,957.0	75,021.0	76,671.0	60,536.0	58,609.0	76,671.0
Munich, n=20								
Mean	45,283.2	45,652	47,134.7	48,382.0	48,223.6	37,981.4	32,709.4	43,609.8
Std. Dev.	15,477.2	15,632	15,891.2	16,041.7	16,657.0	12,730.1	11,739.7	15,964.0
Obs.	1,676.0	1,680	1,664.0	1,664.0	1,682.0	1,682.0	1,682.0	11,730.0
Min	9,720.0	3,620	5,367.0	5,924.0	6,819.0	5,574.0	4,044.0	3,620.0
Max	77,810.0	81,062	82,570.0	88,091.0	87,469.0	87,787.0	61,615.0	88,091.0

4 Data

4.1 Traffic Data

We obtain hourly vehicle traffic counts for the five PM seasons from January 2016 through December 2019 for 46 automatic traffic counters (ATCs) operated by the City of Stuttgart's Integrated Traffic Control Center (*Integrierte Verkehrsleitzentral*, IVLZ) and for 30 ATCs from the Federal Highway Research Institute (*Bundesanstalt für Strassenwesen*, BaSt) located in Stuttgart and Munich. Although we also acquire data from January 2020 through April 2020, we exclude this from our analysis due to the unprecedented effect of COVID-19 lockdowns on mobility and the city's announcement in January 2020 that the DDA program would conclude after the 2019-2020 PM season.

In our dataset, daily counter-level traffic flows are only recorded as the sum of twenty-four hourly counts if data are available for all 24 hours of a day, otherwise they are recorded as missing. Of 55,708 possible counter-day observations spanning 76 counters and 733 particulate matter season days, we ultimately observe 39,403 vehicles per counter-day observations (70.7% of all possible counter-days). Although the share of missing data is considerable for some ATCs, we do not believe that there is a systematic pattern of missing data that would affect our empirical analysis.

On average, 18,238 vehicles pass each Stuttgart ATC each day, with traffic increasing moderately (+6.5%) over the course of the work week before dropping off on Saturdays (-14.5%) and more considerably on Sundays (-30%) relative to Mondays. Public and school holidays also have considerably lower traffic levels (-18.4%) compared to non-

[26]This can be seen in expression 5 by differentiating traffic Q^D with respect to (falling) emotional cost $-E$: $-\frac{dQ^D}{dE} = \frac{G+p^{ND}\delta}{(\tau t^D - E)^2} > 0$.

holidays. Traffic flows are also subject to daily shocks (e.g. accidents, congestion), weekly and monthly variation (e.g. short-term construction sites, traffic re-routing), seasonality, and long-term shifts in road usage (e.g. vehicle bans, road closures, new road infrastructure, transit alternatives, macroeconomic shocks).

Figure 4 maps Stuttgart ATCs and categorizes them into "center" counters located within five kilometers of Stuttgart's administrative centroid (n=19) and "periphery" counters located five kilometers to ten kilometers from the centroid (n=37). The inner five kilometer radius proxies for the AQA's target region in the city center, which is located at the middle of a basin and contains the Neckartor alert trigger PM monitor. The periphery counter group from five kilometers to ten kilometers contains many of the closest park-and-ride locations to the city center, where, on DDA days, car commuters can take subsidized public transit for the final leg of their commute to reach the city center. Periphery traffic flows are considerably higher (20,002 vehicles per counter-day) than city center traffic flows (14,465 vehicles per counter-day).

The properties of our traffic data limit the scope of our analysis in three ways. First, we observe aggregate traffic counts per ATC and cannot identify individual intensive and extensive driving margins. That is, we cannot decipher between a relatively small set of automobiles on the road being driven more intensively (i.e. high daily vehicle kilometers traveled per car) and a proportionally larger set of automobiles being driven relatively less intensively (i.e. fewer daily vehicle kilometers traveled per car). Second, we are not able to observe individual-level modal switching. That means we can only assess the DDA's impact on driving reductions but not on the AQA's other recommended behaviors like using public transit or cycling.[27] Third, our data set consists of traffic flows for a small subset of all streets in Stuttgart, but we do not believe this is a relevant limitation to our data. The 56 Stuttgart ATCs we use in our analysis are distributed across 28 sites, which we believe are representative of overall traffic conditions in Greater Stuttgart as they are dispersed across diverse road types, along key traffic arteries, and in different cardinal directions from the city center.

Table 2: Summary Statistics: Covariates by City and Stuttgart DDA Status

	Stuttgart			Munich			Difference	
	(1) DDA Mean	(2) No DDA Mean	(3) t-Test (2)-(1)	(4) DDA Mean	(5) No DDA Mean	(6) t-Test (5)-(4)	(7) t-Test (1)-(4)	(8) t-Test (2)-(5)
Temperature ($°C$)	4.38	6.20	1.83***	3.47	5.58	2.11***	-0.91	-0.62*
Rainfall (mm)	0.14	1.58	1.44***	0.21	1.58	1.37***	0.07	-0.01
Snowfall (mm)	0.00	0.00	0.00	0.01	0.04	0.03	0.01	0.04
Sleet (mm)	0.04	0.33	0.29***	0.06	0.79	0.73***	0.02	0.46***
Rel. Humidity (%)	73.93	77.47	3.54***	75.67	76.33	0.66	1.74	-1.14
Sunshine Hours	5.13	2.34	-2.79***	4.90	2.43	-2.47***	-0.23	0.09
Wind (km/h)	2.57	3.37	0.80***	2.33	3.43	1.09***	-0.24**	0.06
PM10 ($\mu g/m^3$)	37.74	19.43	-18.32***	31.24	18.10	-13.14***	-6.50***	-1.32
Holiday (=1)	0.06	0.28	0.22***	0.09	0.33	0.24***	0.03	0.05
Days	250	483	733	250	483	733	500	966

Notes: Columns 1 and 4 report mean covariates in Stuttgart and Munich, respectively, on days when a don't drive appeal (DDA) has been called in Stuttgart. Columns 2 and 5 report mean covariates in Stuttgart and Munich, respectively, on days when a DDA has not been called in Stuttgart. Columns 3 and 6 report the results of two-sample t-tests comparing differences in means between DDA days and non-DDA days for each city. Columns 7 and 8 report the results of two-sample t-tests comparing differences in means between Stuttgart and Munich covariates on DDA days and non-DDA days, respectively. Significance level: * = p <0.05, ** = p <0.01, and *** = p <0.001

4.2 Weather, Pollution, and DDA Status

We follow the existing AQA literature to control for daily weather factors which may influence driving and AQA activation such as temperature, precipitation by type, and wind speed. We retrieve weather data for the Schnarrenberg weather station from DWD Open Data (see location in figure 4). Local authorities use atmospheric data from this weather station to evaluate the AQA conditions, so we believe it is most relevant when controlling for program determinants. Furthermore, this weather station is located centrally in Stuttgart, so we assume that weather conditions there are the best available measure of meteorological factors that might influence commuters.[28] Air pollution data come from the Baden-Württemberg State Institute for the Environment, Survey and

[27] We have inquired at the city of Stuttgart and its public transportation partners about alternative transit records. The city nor its public transportation partners maintain turnstiles at public transit stations that would deliver daily public transit statistics. Available overall monthly ticket sales do not have the temporal or spatial resolution necessary for our analysis. The city does track daily cycling counts at two automatic bicycle counters over the time period of interest, and this data could be exploited in a future extension of our analysis.

[28] We could merge weather data from the Stuttgart airport weather station at the city's southern periphery to ATCs located close to it, but we believe weather conditions at the Schnarrenberg weather station in Stuttgart are most indicative of commuters' expectations about the city center. Moreover, we don't expect that accounting for differences in local weather variation over such short distances (i.e. less than fifteen kilometers) would significantly affect our results.

Nature Conservation (*Landesanstalt für Umwelt Baden-Württemberg*, LUBW), which monitors PM_{10} concentrations in the city center (see location in figure 4). We perfectly observe DDA status and manually input it from an official Stuttgart website as a binary variable that equals one on days when a DDA is called and zero otherwise (figure 5).

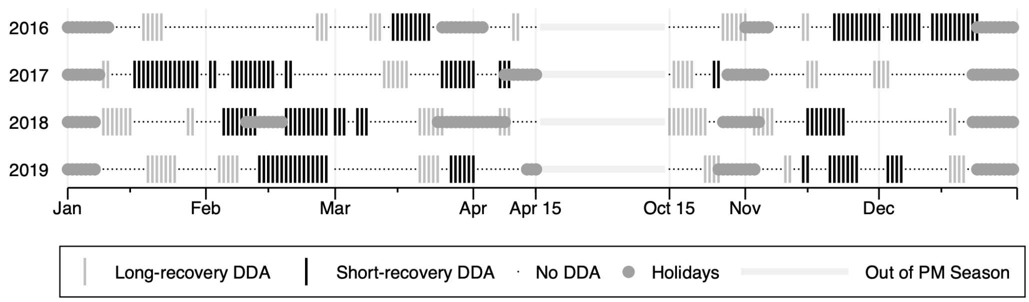

Figure 5: DDA days split by median recovery time (9 days) from January 2016 through December 2019. Data source: City of Stuttgart and own calculations.

In comparison to other DDAs and AQAs studied in the literature, Stuttgart's DDA is implemented very frequently and for long durations.[29] Over 733 possible AQA days from January 2016 through December 2019, Stuttgart authorities broadcast a DDA on 250 days (34%) in 44 multi-day DDA events with an average duration of 5.7 days. Table 2 shows that DDA days are, on average, colder, less windy, less humid, sunnier, and more polluted in Stuttgart than non-DDA days, which is in line with the AQA design. DDA days also experience less non-snow precipitation (i.e. rain or sleet) and fewer heavy non-snow precipitation events. DDA days are typically preceded by days with similar weather and pollution levels, while the same holds for non-DDA days. Authorities are also less likely to call DDAs on public and school holidays, possibly due to lower expected traffic levels on these days. Figure 5 shows that few DDAs fall on public or school holidays (14 DDA days during 149 holidays, 9.4%) compared to non-holidays (236 DDA days during 584 non-holidays, 40.4%). For this reason, we believe that local authorities may systematically treat holidays differently than non-holidays, so we remove public and school holidays from parts of our analysis. Table 4 shows that authorities often announce DDAs on weekends and at the beginning of the week, leading a large share of DDAs to start on Mondays, Tuesdays, and Wednesdays. DDAs most frequently end on

[29]For example, in Cutter and Neidell (2009) about 4.5% of days in San Francisco, USA are treated with an *Spare the Air* alert, in Saberian et al. (2017) about 1.3% of days in Sydney, Australia experience an ozone alert day, and in Tribby et al. (2013) about 16% of PM season days have either a yellow or red AQA. In Sexton (2012), the likelihood of two consecutive *Spare the Air* days is just 0.6%.

Saturdays (33%, 12 of 36 possible days). Overall, there is a fairly uniform distribution of DDA days across the working week with weekends being treated with DDAs less often than weekdays.

5 Empirical Framework

5.1 OLS Estimation

We begin by estimating the impact of Stuttgart's DDA on traffic levels using an ordinary least squares (OLS) regression model described by the following equation:

$$log(y_{i,t}) = \beta_1 DDA_t + \delta_1 M_t + \gamma_i + \phi_t + \epsilon_{i,t}, \tag{6}$$

where $y_{i,t}$ is the number of vehicles passing counter i on date t, and β_1 estimates the DDA effect as the percent difference in daily traffic counts between DDA days and non-DDA days.[30] The variable of interest, DDA_t, is a binary variable that takes on a value of one on DDA days and zero otherwise. We include weather controls (M_t) to account for same-day weather conditions in Stuttgart.[31] Counter-level fixed effects (γ_i) account for counter-specific traffic levels and year-month time fixed effects (ϕ_t) flexibly capture trends and temporal discontinuities that might influence overall car use from month-to-month (e.g. construction, varying public transit prices, vehicle bans, new transit infrastructure, etc.). We also include day-of-the-week dummies to account for weekly traffic cycles and holiday dummies to capture changes in traffic levels during holidays and vacation periods.

Our estimation equation tests the null hypothesis that the DDA effect is equal to zero ($H_0 : \beta_1 = 0$), or, in other words, that traffic flows in Stuttgart do not differ significantly on days when a DDA is broadcast. If, as intended, car use decreases on DDA days, the DDA coefficient must be negative ($\beta_1 < 0$) and differ significantly from zero. In our setting, traffic counts are correlated over time[32] and across ATCs.[33] In the regression

[30] Log-scaling the outcome variable leads the coefficient of interest to approximately estimate a percentage change rather than an absolute change in levels.

[31] We follow the literature on air quality alerts and transportation choice in including precipitation, temperature, wind speed as control variables. In addition to absolute precipitation by type, we also include squared terms for rainfall (mm^2), snowfall (mm^2), and sleet (mm^2).

[32] We would like to test for serial correlation but the gaps in our dataset and the unbalanced nature of our panel prevent us from successfully running common STATA commands like xtserial, xtqptest, and xtistest. It is unclear how to appropriately test for this given our dataset.

[33] We implement a CD-test for cross-sectional dependance (Pesaran, 2020) in the outcome variable, $y_{i,t}$, and reject the null hypothesis of cross-sectional independence (p-value < 0.001).

model defined by equation (6), we employ heteoscedasticity-robust Huber-White standard errors and adjust for serial correlation and cross-sectional dependence by clustering standard errors at the counter level. As we explain in section 5.2, numerous factors could plausibly bias these OLS point estimates, so we caution against interpreting regression results from equation 6 as causal estimates. We describe these identification challenges in the following subsection and turn to a difference-in-difference (DiD) estimation strategy in section 5.3.

5.2 Identification Challenges

The non-random assignment of DDA treatment from day to day in Stuttgart presumably biases our OLS estimates for several reasons. First, DDAs are broadcast based on a set of multi-day atmospheric and pollution determinants, meaning that DDA days are a non-random selection of days that are colder, less windy, less humid, sunnier, and more polluted than non-DDA days as shown in table 2. Unlike previously-studied AQAs (Cutter and Neidell, 2009; Noonan, 2014), Stuttgart DDA treatment is also not determined by a single contemporaneous atmospheric parameter (e.g. a pollution threshold value which may be imperceptible at the margin). Furthermore, treatment conditions must be satisfied for a prolonged period to activate, and, when activated, treatment remains in effect for at least two days independent of how treatment conditions actually develop.[34] Meteorological treatment determinants presumably also directly influence transportation demand and could thereby confound DDA effect estimates. In particular, persistent weather conditions, which are endogenous to the treatment protocol, may correlate with car trip demand and modal switching. For example, some motorists may be more likely to naturally choose transit alternatives such as public transit or cycling during prolonged dry, sunny weather, while such conditions also increase the likelihood that a DDA is called, potentially biasing our DDA effect estimates downward. Selecting a meaningful control group of untreated multi-day events with similar weather patterns would best isolate the DDA effect, but the small number of in-sample control days during the policy implementation period limits the statistical power of such an approach. Instead, we control for these factors in our OLS regressions by including same-day co-

[34] The AQA program design complicates identification via a standard regression discontinuity design as in Cutter and Neidell (2009) or Noonan (2014). For DDA treatment to activate, multiple atmospheric thresholds must be fulfilled simultaneously and multiple pathways exist (see section 2). Hence, there is no single cut-off point we could exploit as a policy discontinuity. Other feasible identification strategies in our setting include: i) synthetic control with never-treated German cities, ii) difference-in-difference comparison with pre-program (i.e. pre-2016) traffic in Stuttgart during multi-day periods that fulfilled the meteorological conditions, or iii) exploiting alert designation errors (e.g. false positives, false negatives).

variates, adding first-day and second-day lagged meteorological variables, and flexibly controlling for trends over time with monthly and weekly fixed effects.

Pollution may also confound our OLS estimates through similar channels. For example, even in the absence of a DDA program, high pollution levels may induce some motorists to naturally avoid pollution and change car trip demand. It is not clear ex ante which strategies individuals in Stuttgart might employ to reduce pollution exposure and how this affects car trip demand, but causal DDA treatment estimates would need to disentangle behavioral responses to high pollution from those due to an active DDA. We note that a considerable share of untreated days have high pollution levels (due to the no rainfall conditions in the treatment protocol) and use controls for contemporaneous pollution levels and their lags in our OLS regressions to account for the net effect of pollution avoidance strategies on car trip demand independent of DDA treatment status.[35]

Another source of bias arises if local authorities' expectations about car trip demand affect their decision whether to call a DDA or not. Local authorities have some discretion when evaluating AQA conditions and could decide not to call an alert if they don't see it as worthwhile, even though the alert conditions are technically satisfied. For example, in section 4 we demonstrate that local authorities are less likely to broadcast a DDA during school or public holidays presumably because they already anticipate low traffic levels on these days. If authorities systematically under-assign DDAs on days with lower traffic levels, and we do not account for this, our OLS estimates would be biased upward. But, we cannot observe all of the factors leading authorities to diverge from the AQA design rules or policy-makers' traffic expectations, so we prefer OLS specifications that remove periods with traffic outliers such as holidays and weekends.

Reverse causality between the outcome of interest, car trip demand, and DDA treatment status could also plausibly threaten the internal validity of our OLS estimates. A larger or smaller number of cars driving in Stuttgart could, by increasing or decreasing total vehicle emissions, cause PM_{10} levels to rise or fall relative to the DDA's 30 $\mu g/m^3$ primary sub-condition threshold and switch the DDA on or off. However, we note that car trip demand, and thereby its subsequent effect on pollution, has no influence over the necessary second sub-condition of primary DDA condition 1, namely whether rainfall is anticipated or not, nor over the remaining five atmospheric conditions which can acti-

[35] Pollution avoidance strategies can plausibly affect overall car trip demand. For example, if a significant share of individuals respond to high pollution levels by staying at home indoors and abstaining from travel, car trip demand would fall. Alternatively, if a substantial number of commuters drive more in cars to protect themselves (with filtered, recirculated air) rather than walking and using public transit outdoors or drive out of the city to avoid pollution, car trip demand would increase.

vate DDA treatment independent of PM_{10} pollution levels. Considering this embedded exogeneity in the DDA treatment protocol, previous findings of moderate to negligible impacts of DDAs on driving in other settings, and looking ahead to the magnitude of our estimates presented in section 6, we believe it is improbable that marginal changes to car trip demand cause treatment status to change.

Finally, the announcement of an upcoming DDA may change motorists' choices until the DDA actually takes effect (i.e. on or preceding the issue or bridge day) or after the end of a DDA (i.e. on the first or second recovery day). We cannot observe whether individual motorists take additional trips on issue and bridge days or on the first recovery days after a DDA to avoid taking trips during the DDA, but such a scenario would bias our overall DDA effect estimates downward. We account for these anticipatory and posttreatment effects by removing issue, bridge, the first two recovery days from our sample in some OLS specifications and inspecting for parallel time trends in the following section.

5.3 Difference-in-Difference Estimation

To recover the causal effect of DDAs on car trip demand, we rely on a difference-in-difference (DiD) approach that uses ATCs in the metropolitan city of Munich in the neighboring state of Bavaria as a never-treated control group for Stuttgart ATCs. Compared to OLS estimation, the main advantage of this approach is that we can account for day-to-day variation in car trip demand driven by unobservable factors common to Munich and Stuttgart. We believe that Munich is an appropriate comparison for Stuttgart in our setting because it has a similarly sized metropolitan population, pollution routinely exceeds annual EU air quality limits, and it has a similarly dense public transit network, but it never implemented a DDA program. Munich is located over 160 kilometers from Stuttgart, so we believe this minimizes the likelihood of treatment spillovers from Stuttgart in violation of the stable unit treatment variable assumption (SUTVA). We compare traffic at ATCs within ten kilometers from the Stuttgart geographic centroid with a control group of never-treated ATCs located within ten kilometers of the Munich geographic centroid. This enables us to shed light on treatment effect heterogeneity over DDA event time and recovery duration.[36]

A key assumption for successfully identifying causal DiD effects is that Munich is a

[36]Previous research on AQAs highlighted some important heterogeneities in alert effectiveness. For example, Tribby et al. (2013) find evidence of spatial displacement effects where traffic increases at Salt Lake City, USA's periphery on alert days and Saberian et al. (2017) and Graff Zivin and Neidell (2009) find evidence of alert fatigue on the second day of ozone alerts.

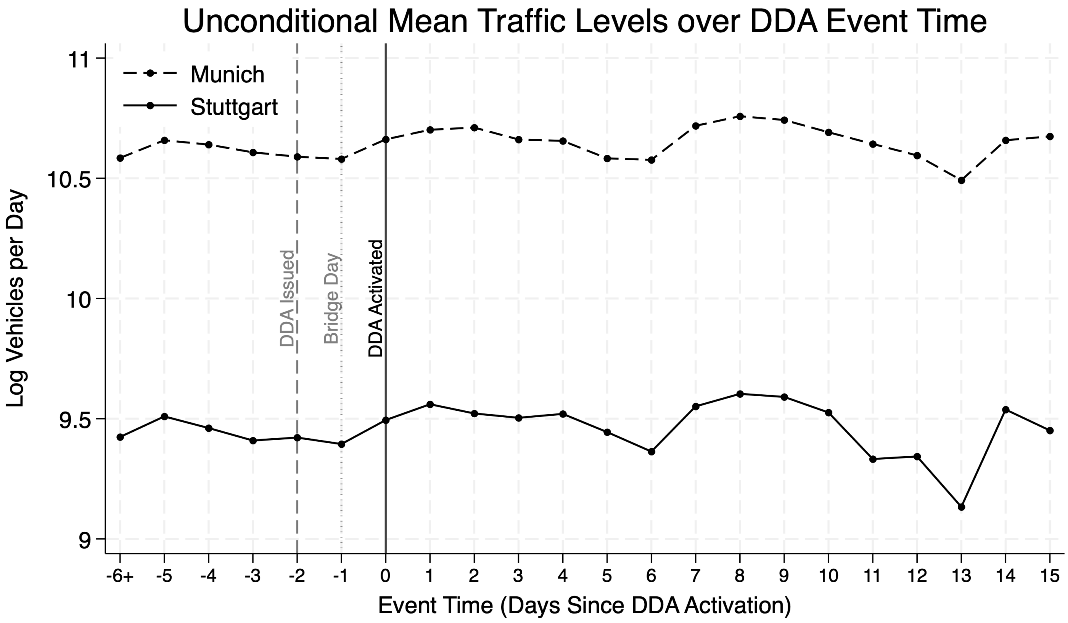

Figure 6: This figure plots mean traffic levels across all counters in Stuttgart and Munich within ten kilometers of each city's centroid over don't drive appeal (DDA) event time. The pretreatment period includes up to ten days before the activation day. The treatment period includes all DDA days including those when the end of the DDA event has already been announced.

meaningful treatment counterfactual for Stuttgart or, in other words, that traffic trends in Stuttgart develop in parallel with Munich would the DDA policy not be implemented (Angrist and Pischke, 2009). To test this, we begin by visually inspecting figure 6, which plot trends in mean logged unconditional traffic levels in the two cities on the same calendar days averaged over Stuttgart DDA event time. In the pre-DDA window in figure 6, which spans from 6+ days to 1 day (event time: -6+ to -1) before DDA activation, mean traffic levels in both Stuttgart and Munich trend downward at a similar rate from five days before AQA activation (event time: -5) through the bridge day (event time: -1). In the treatment period (event time: 0-15), traffic levels continue to develop in a similar manner.

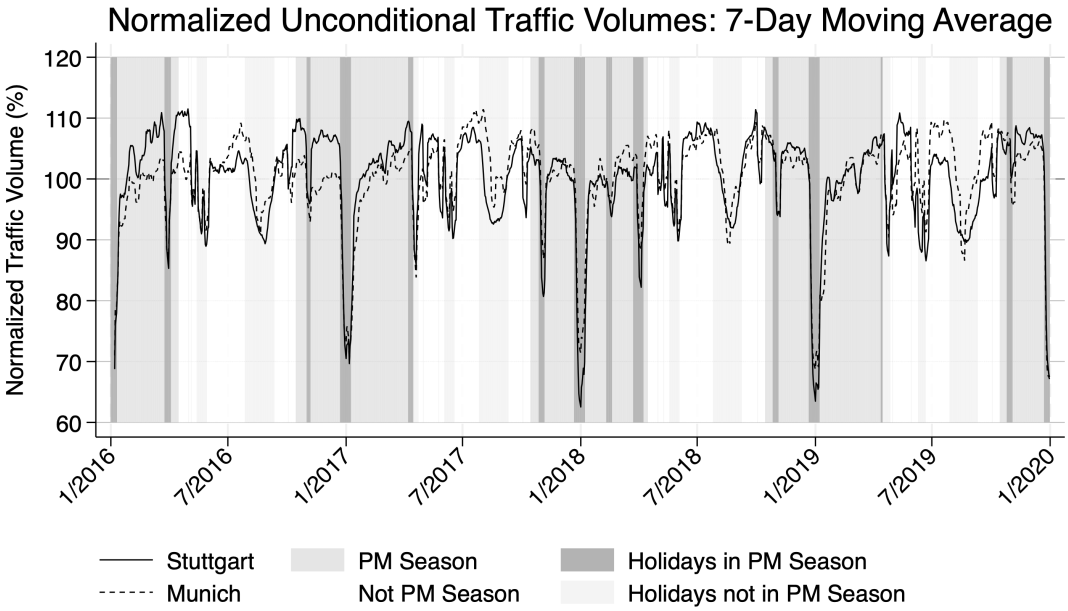

Figure 7: Seven-day moving average of normalized traffic volumes.

In building our argument for common trends between Stuttgart and Munich, we next refer to figure 7, which depicts normalized traffic trends in each city.[37] Average traffic patterns in Munich trace Stuttgart traffic patterns very well over time as we believe they capture previously unexplained daily and week-to-week variation in economic activity in Stuttgart. There are strong seasonal trends but most striking are symmetrical drop-offs in and reversions to mean traffic levels during and after holiday periods. While controls

[37] We normalize by calculating in percentage terms how much each day each ATC deviates from its own mean traffic level and then averaging this across all ATCs in each city.

for holiday periods and monthly temporal fixed effects would flexibly capture some of this variation and seasonality, there is a concern that dramatic changes in traffic levels, as depicted in figure 7, might be absorbed into DDA effect estimates if fixed effect are temporally coarse. Calendar date fixed effects in counter-level DiD specifications will resolve this by capturing the day-to-day variation in traffic common to both cities. For the majority of the program period traffic trends in figure 7 are closely linked, but there is a noticeable spread in our measure of Stuttgart and Munich traffic levels in the 2016 PM seasons. Counter level fixed effects will help to absorb these differences.

Furthermore, we argue that Munich ATCs are a suitable control group for Stuttgart ATCs because Munich commuters are exposed to very similar same-day meteorological and pollution conditions. Table 2 in section 4 includes summary statistics for these covariates and two-sample t-tests for differences between the two cities. Column 7 shows that there are no statistically detectable differences in temperature, rainfall, snowfall, sleet, relative humidity, or sunshine hours between the two cities on days when a DDA is called in Stuttgart. Munich is, however, somewhat less windy and exposed to about 6.5 fewer $\mu g/m^3$ of PM_{10}, on average during DDAs. Figure 8 sheds further light on trends in PM_{10} pollution over DDA event time. Pollution develops in parallel in both cities in the pre-treatment period (event time: -6+ to -1), but on the day that the DDA takes effect, PM_{10} levels in Stuttgart jump nearly 9 $\mu g/m^3$ higher than in Munich. Presumably, this is linked to Stuttgart's geographic position in a bowl-shaped valley that better traps pollution than Munich's morphology. However, mean pollution levels remarkably evolve in the same fashion in Stuttgart and Munich over event time. Ultimately, differences in pollution levels don't appear to be substantial, and controlling for same-day differences should address concerns about comparability.

To build our DiD models, we rely on a standard two-way fixed effects (TWFE) specification as a baseline:[38]

$$log(y_{i,t}) = \beta_1 DDA_t \times Treated_i + \gamma_i + \phi_t + \eta \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{7}$$

where DDA_t is a dummy variable that designates whether a DDA has been activated on

[38] The recent TWFE literature has identified shortcomings to TWFE estimators in treatment settings that extend beyond the classic two period and two group setup (Roth et al., 2023). Our setting has the canonical two main groups but many pretreatment and posttreatment periods, repeated treatments of varying duration, and plausible heterogeneous treatment effects between treated units (i.e. between Stuttgart ATCs). However, there are no variations in treatment timing between units, which mitigates the concern that our point estimates may be contaminated by effects from other time periods (Sun and Abraham, 2021). Moreover, our control group of Munich ATCs remains never-treated throughout. Because there is currently no estimator tailored to our empirical setting, we carefully select a control group, demonstrate parallel trends, and check for anticipation effects.

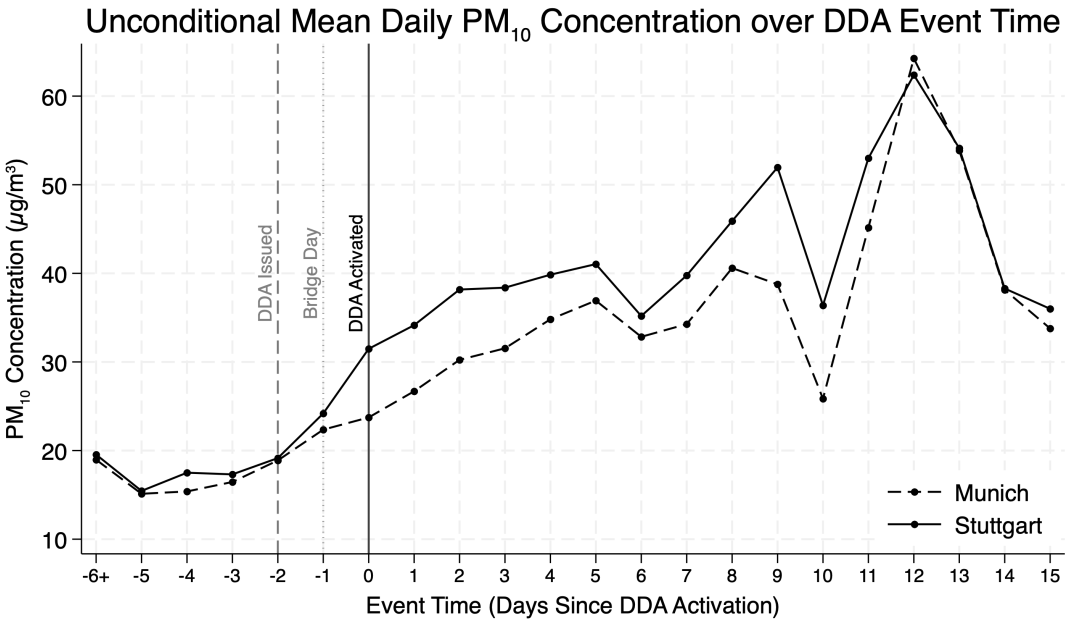

Figure 8: This figure plots mean daily PM_{10} pollution concentrations across all pollution monitors in Stuttgart and Munich over don't drive appeal (DDA) event time. The pretreatment period includes up to ten days before the activation day. The treatment period includes all DDA days including those when the end of the DDA event has already been announced.

that day, $Treated_i$ is a dummy variable for whether the ATC belongs to the treatment group (e.g. within ten kilometers of the Stuttgart city centroid), γ_i are ATC fixed effects, ϕ_t date fixed effects, and $\mathbf{X}_{i,t}$ a vector of city-specific weather and pollution controls and lags. β_1 estimates the average percentage difference in traffic levels between treated and untreated ATCs.

In a subsequent specification, we spatially disaggregate our DDA effect estimates by interacting the $DDA_t \times Treated_i$ with counter-specific dummy variables (ATC_i) to estimate counter-specific DDA effects. We then create binary variables for DDA event time and between event recovery time and interact these with $Treated_i$ to examine temporal heterogeneity in DDA effectiveness.

5.3.1 Dynamic Treatment Effect Estimation

We create D_j, a set of dummy variables corresponding to event time days over the duration of each DDA event ranging from ten days before the activation day through the last DDA day. Calendar days that are not within these windows are removed from this part of the analysis. We group pretreatment days more than six days before the issue day (day -6+, j = -6) and posttreatment days on the fifth or later day of a DDA (day 5+, j = 5).[39] Accordingly, we replace the DDA_t variable in equation 7 with D_j and test for DDA effect dynamics over event time by estimating the following regression equation:

$$log(y_{i,t}) = \sum_{j \in -6,\ldots,0,\ldots.,5} \beta_j D_{i,t-j} \times Treated_i + \gamma_i + \phi_t + \eta \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{8}$$

where each β_j corresponds to the percent change in traffic between treated and untreated ATCs on event time day j. Equation 8 include a vector of city-specific weather and pollution covariates (X_t) to control for differences in same-day weather conditions.

5.3.2 Dynamic Posttreatment Effect Estimation

We similarly employ a set of D_k dummy variables to test for posttreatment effect dynamics when the DDA is terminated. This model is described by:

$$log(y_{i,t}) = \sum_{j \in -5,\ldots,0,\ldots.,2} \beta_k D_{i,t-k} \times Treated_i + \gamma_i + \phi_t + \eta \mathbf{X}_{i,t} + \epsilon_{i,t}, \tag{9}$$

[39]For our regressions, we consider the day before the issue day ($j = -3$) as the baseline.

and replaces D_j in equation 8 with D_k, which is relative to the first posttreatment day without an alert. We consider an event time window from five or more days before day the DDA is lifted (day -5+, k=-5) including only treated days to two or more days after the DDA is no longer in effect (day 2, k=2) and no new DDA has been announced. Two transition days (day -2 and day -1, k=-2 and k=-1, respectively) when the DDA is still in effect but it has been announced that it will be lifted precede the first post-DDA day (day 0, k=0).[40]

5.3.3 Recovery Time Effect Estimation

As depicted in figure 5, we split DDA events into those with less than a median recovery time since the preceding DDA (short-recovery: < 9 days) and DDA events with a greater than median recovery time (long-recovery: ≥ 9 days). For each DDA event, we construct a window around each DDA activation day that spans up to ten days before the activation day until the last DDA day.[41] We then generate a binary variable, $Recovery_l$, corresponding to whether each calendar date is part of a short recovery DDA window ($Recovery_l = 0$) or a long recovery DDA window ($Recovery_l = 1$). Days that are not in a short or long DDA window are omitted from the analysis. In a triple-difference specification, we fully interact the temporal DDA treatment term (DDA_t), the Stuttgart versus Munich treatment group term ($Treated_i$), and the recovery split term ($Recovery_l$) as described by the following equation:

$$\begin{aligned} log(y_{i,t}) = \beta_1 DDA_t + \beta_2 Treated_i + \beta_3 Recovery_l + \beta_4 Recovery_1 \times Treated_i \\ + \beta_5 Recovery_1 \times DDA_t + \beta_6 Treated_i \times DDA_t \\ + \beta_7 Recovery_1 \times Treated_i \times DDA_t + \gamma_i + \phi_t + \eta \mathbf{X}_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{10}$$

All remaining regressors from equation 7 are also included. To test for spatial heterogeneity in recovery effects, we also separately estimate equation 10 for i) city center ATCs within five kilometers from the Stuttgart centroid and ii) periphery ATCs located between five kilometers and ten kilometers from the Stuttgart centroid.[42]

[40]The day before the issue day ($j = -3$) is the baseline in our regressions.

[41]Preceding DDAs take precedence, so the pretreatment period is smaller for DDAs with shorter recovery periods. Ultimately, DDA event windows include for long recovery DDAs a total of 277 calendar days and for short recovery DDAs 226 calendar days.

[42]In both regressions, we consider all Munich ATCs as the control group because only two Munich ATCs are within five kilometers of the city center.

6 Results

6.1 Overall DDA Effect

Table 3: OLS and DiD Regression Results: Overall DDA Effect

	(1) OLS b/se	(2) OLS b/se	(3) OLS b/se	(4) OLS b/se	(5) DiD b/se	(6) DiD b/se
DDA Active (=1)	0.0100***	-0.0033	0.0054**	-0.0056*	0.0094	-0.0081
	(0.0027)	(0.0034)	(0.0023)	(0.0030)	(0.0074)	(0.0060)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lags	Yes	Yes	Yes	Yes	Yes	Yes
All Days	Yes	No	Yes	No	Yes	No
Time FE	YM	YM	YMxATC	YMxATC	Date	Date
Unit FE	ATC	ATC	ATC	ATC	ATC	ATC
# ATCs	56	56	56	56	76	76
Observations	27,252	12,362	27,243	12,340	38,818	17,342

Note: Dependent variable is logged vehicles per counter-day. Controls include contemporaneous weather and pollution variables. Lags are two days of lagged weather and pollution covariates. Regressions either include all 733 PM season days or 331 non-holiday weekdays excluding DDA transition days. Unit fixed effects are always at the automatic traffic counter level. Time fixed effects are either year-month ("YM"), year-month by ATC ("YMxATC"), or calendar date. Standard errors clustered on counter in parentheses. *=p<0.1, **=p<0.05, ***=p<0.01.

Our regression results show that the overall DDA effect is of small to negligible magnitude across a variety of model specifications. Table 3 displays DDA effect point estimates for different specifications of three different regression models: 1) OLS with year-month and counter fixed effects, 2) OLS with a full interaction of year-month and counter fixed effects, and 3) a TWFE DiD specification with calendar date and counter fixed effects that uses Munich ATCs as a never-treated control group. For each model, we display results for the full sample of 733 days and then restrict the sample to 331 normal, non-holiday weekdays excluding DDA termination transition days.

Across all models, DDAs affect Stuttgart traffic levels by -0.56% to +1.00% and some specifications estimate a statistically significant overall effect at odds with DDA goals. In column 4, our preferred specification within OLS, a model that includes contemporaneous and two days of lagged weather and pollution controls, counter-level fixed effects, year-month fixed effects, and counter-year-month fixed effects and omits weekends, holidays, and DDA termination transition days, estimates that the DDA leads to a traffic decrease of about 0.56% on DDA days, or about 102 fewer vehicles per counter-day.

This estimate is statistically significant at only the 10% significance level. Back-of-the-envelope calculations equate this DDA effect with a net decrease of about 2,139 motorists in Stuttgart on DDA days.[43] Our main causal estimate in column 6 is a DiD model that uses Munich ATCs as an untreated control group, includes date and counter fixed effects, and excludes weekends, holidays, and DDA termination transition days. Like our preferred specification within OLS, the coefficient of interest corresponds to a decrease of negligible magnitude (0.8% decrease) but this effect is statistically insignificant.

In no specification do we estimate a statistically significant overall traffic reduction stronger than 0.6%. The moderate DDA effect in our main DiD specification and the mixed effects across all specifications suggest that the DDA fails to substantially reduce overall traffic levels in Stuttgart. In the next steps of our analysis, we explore whether these aggregate DDA effect estimates mask differences in DDA effectiveness across geographic space and time.

6.2 Spatially Disaggregated DDA Effects

We spatially disaggregate our main DiD specification by including counter-specific interaction terms regression equation 7 to estimate the daily DDA effect at each ATC location. To explore spatial heterogeneity in DDA effectiveness, we group the 56 counters relative to distance from the Stuttgart center into: i) 19 center locations within five kilometers and ii) 37 periphery sites between five kilometers and ten kilometers. Figure 9 plots individual counter-level DDA effect estimates and group means and median point estimates. With four exceptions, counter-level estimates range from -10% to +10% across all three counter groups, suggesting that local traffic may indeed change substantially on DDA days. Our counter-level estimates show traffic differs statistically at a majority of counters on DDA days. Group mean effects are positive and very similar, but considering that the median center group point estimate is below zero, the DDA may be marginally more effective at reducing city center traffic than traffic at the city's periphery. Moreover, two disproportionately large positive outliers appear to drive the center group mean up. At distances closest to the city center, point estimates seem to reliably be smaller and more often negative. Between five kilometers and ten kilometers, a larger share of ATCs see traffic increases on DDA days, reflected in the positive group median in the periphery counter group.

Figure 13 in appendix D maps the coefficients plotted in figure 9 from our main DiD specification. Again, visual inspection suggests that ATCs located closest to the city

[43]This assumes 382,000 motorists on an average work day.

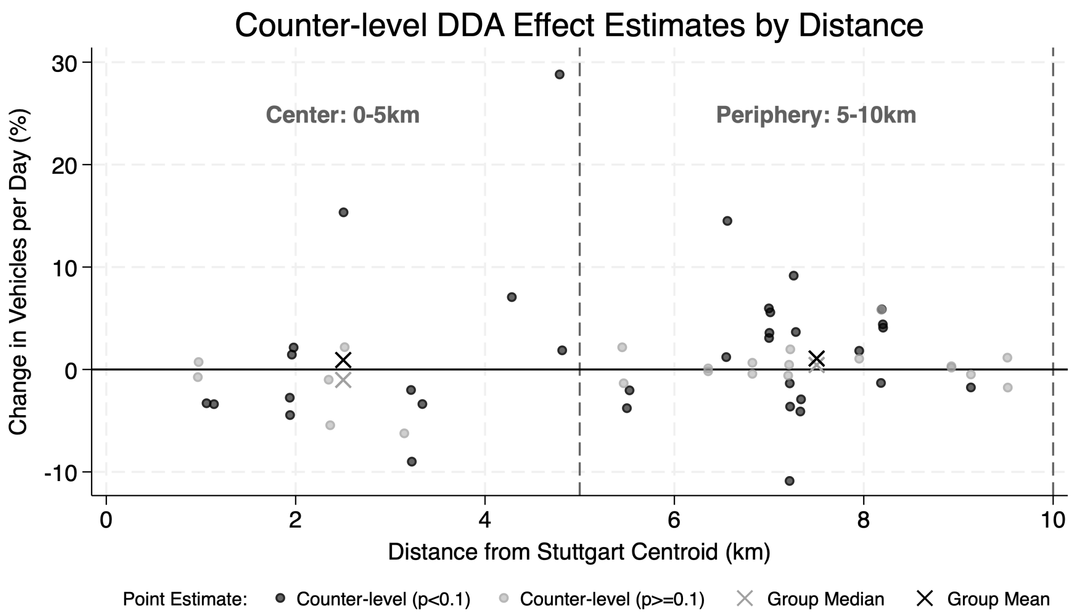

Figure 9: The figure plots counter-level don't drive appeal (DDA) effect point estimates from our main DiD regression model. Stuttgart counters are split into two groups relative to their distance from the city center: i) center counters located within five kilometers and ii) periphery counters located between five kilometers and ten kilometers. For each group, we plot the group mean and median DDA effect point estimate at the group's distance midpoint.

center are most likely to experience statistically significant traffic reductions on DDA days, while positive DDA effect estimates in the center counter group are primarily located on major roads further from the immediate center. In the periphery counter group, a large share of ATCs are located at the city's northern periphery and suggest that traffic uniformly increases along the northern periphery, while similar results appear to hold at the southern periphery. While our analysis lacks sufficient data on traffic flows at the southwestern and northeastern periphery, we do not have any reason to believe that trends there would differ significantly from the periphery effects we observe at other locations.

These spatially disaggregated results indicate that the DDA policy may heterogeneously affect traffic with respect to distance to the city center. While our analysis does not enable us to pinpoint a mechanism underlying this effect, we believe two factors may play an important role. First, commuters and policy-makers may see reducing traffic levels at the city center, where the AQA trigger monitor is located, as the DDA program's ultimate goal and consider traffic reductions at other locations within the city's administrative boundary as secondary. Second, car commuters who want to adhere to the DDA may respond to this spatial differentiation by minimizing their commuting time with alternative transportation modes. For example, they may drive their cars up to the city's periphery or even slightly within the official boundary, park their vehicles there, take advantage of public transit subsidies, and switch to public transit for the remainder of their commute.

6.3 DDA Effect Dynamics

6.3.1 Treatment Effect Dynamics

A plausible mental model of the effects of a DDA on driving decisions hypothesizes possible dynamic effects (see section 3). To explore these, we interact DDA event time terms with the DDA treatment variable in equation (6) to estimate daily DDA effects over DDA event duration. Figure 10 displays DDA effect point estimates for each day of a DDA. Once the DDA takes effect, we find that overall Stuttgart traffic levels drop by over 2% on the first DDA day (event time: 0) and by over 3% on the second and third DDA day (event time: 1 to 2) relative to the counterfactual. We can statistically rule out that the DDA has no impact for each of the first three DDA days at the 95% significance level. On the fourth DDA day and beyond (event time: 3+), the DDA effect drops in magnitude while the fourth and fifth DDA day (event time: 3-4) remain statistically different from zero. DDA effect estimates throughout the treatment period are all in line with the DDA program's intended reduction of traffic volumes. However, the point estimate for the sixth day and beyond (event time: 5+) is relatively large in magnitude, has larger confidence intervals, and is statistically insignificant. Larger variation in program effectiveness during extended DDAs might be driving this, but our small sample of days at the tail end of longer DDAs prevents us from analyzing this more carefully.

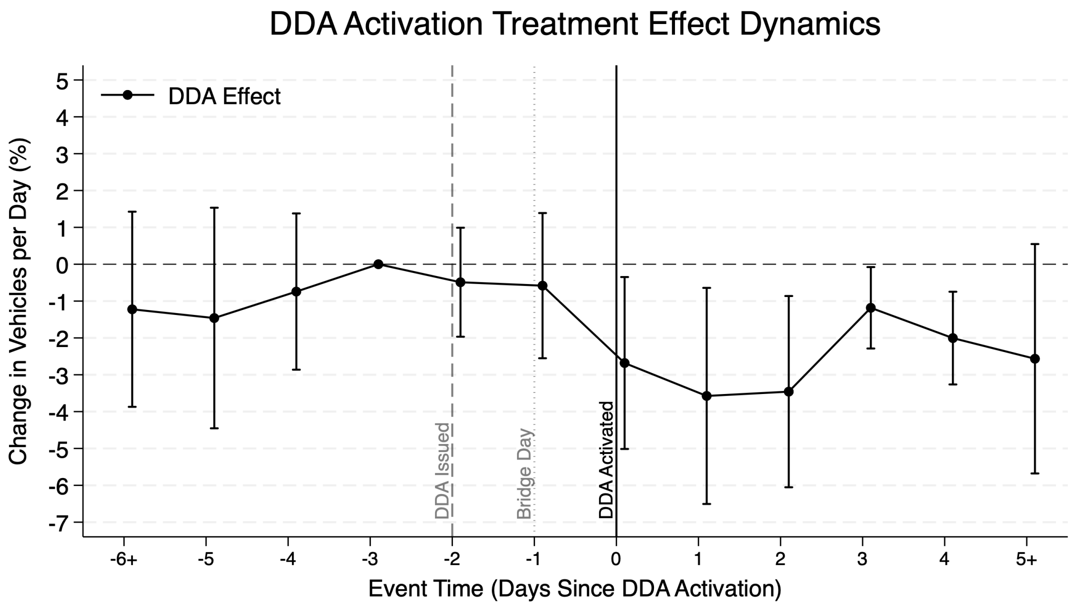

Figure 10: Dependent variable is logged vehicles per counter-day. Regressions include counter and calendar date fixed effects and local weather and pollution controls. Only days with normal weekday traffic are included. Don't drive appeal (DDA) days when the DDA event end date has already been announced and first two days following the event end date are excluded. Treated group includes 56 counters within ten kilometers from Stuttgart city centroid. Control group includes 20 counters located within ten kilometers from Munich city centroid. Standard errors are clustered on counter and 95% confidence intervals are depicted.

We also note that pretreatment coefficients (days j=-6 to j=-1) do not differ significantly from zero, suggesting that average traffic levels in Stuttgart and Munich develop in parallel on days before DDAs are called. Importantly, our point estimates do not provide any evidence of anticipatory effects, even on issue or bridge days when motorists have been informed of the upcoming DDA but have yet not been asked to reduce driving. These results are largely in line with hypothesis 1 of our theoretical framework and demonstrate that DDAs are most effective immediately after being activated.

6.3.2 Posttreatment Effect Dynamics

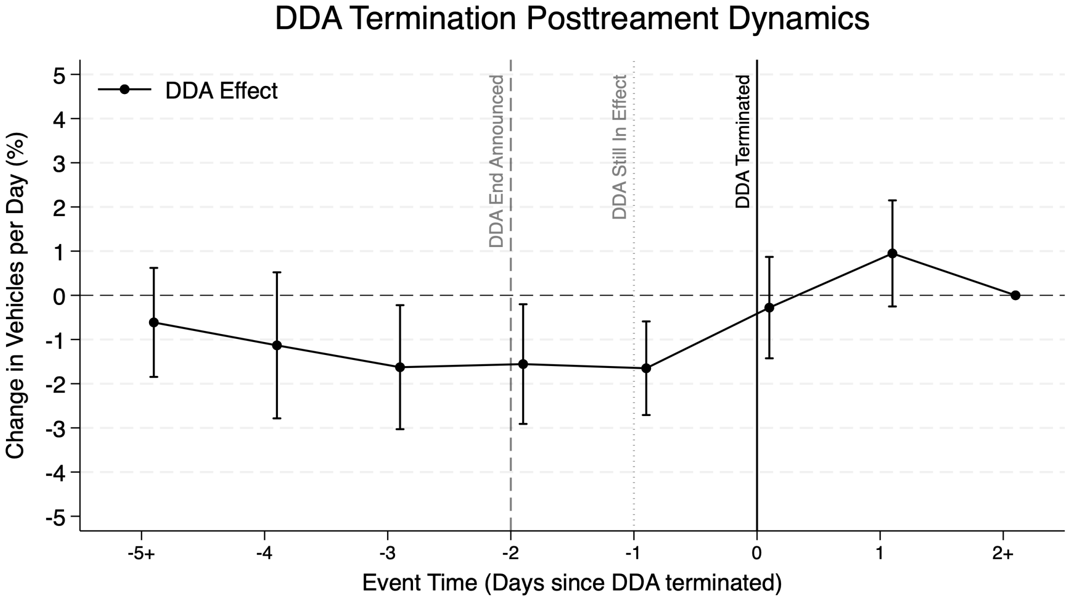

Figure 11: Dependent variable is logged vehicles per counter-day. Regressions include counter and date fixed effects and local weather and pollution controls. Treated group includes 19 center counters within five kilometers of city center and 37 periphery counters five to ten kilometers from Stuttgart city centroid. Control group includes 20 counters located within ten kilometers of the Munich city centroid. Standard errors are clustered on counter and 95% confidence intervals are depicted.

We also examine how DDA effect estimates change when DDA events are terminated. Figure 11 shows posttreatment effect estimates. [44] Starting on the third day before the DDA ends, traffic levels drop by over 1% relative to a baseline of two or more days after the DDA is lifted. This effect remains statistically significant for the last two DDA days,

[44]In this post-DDA analysis, we estimate a DDA effect during the treated period (k=-5+ to k=0) of between -0.5% and -1.75%. While the signs on the DDA treatment effect estimates align with the direction of our results from figure 10, the magnitude of our estimates differs because we look at treatment days relative to the end of the DDA rather than the beginning. In other words, we count backward from the event time day that the DDA is terminated. In the posttreatment analysis a DDA treatment day three days before the DDA is lifted (k=-3) could have originally been on one of many different DDA days relative to the DDA activation day depending on how long the DDA lasted. For example, it could have been on first day of a three day DDA or on the seventh day of a ten day DDA.

including the day when authorities have already announced a DDA end date (always two days before the DDA is actually lifted). Once the DDA is no longer in effect and DDA messaging subsides, traffic levels return to baseline levels and the DDA effect does not differ statistically from zero. These results affirm our prediction from hypothesis 2, which postulates that DDAs are effective when commuters can expect when the DDA will be lifted. On the first posttreatment day, we can rule out changes in traffic above 1% in magnitude at the 95% significance level, while the higher point estimate and wider confidence interval on the second posttreatment day shows that traffic may rebound after the DDA is lifted, providing some suggestive evidence in favor of hypothesis 4.

6.3.3 Recovery Time Effects

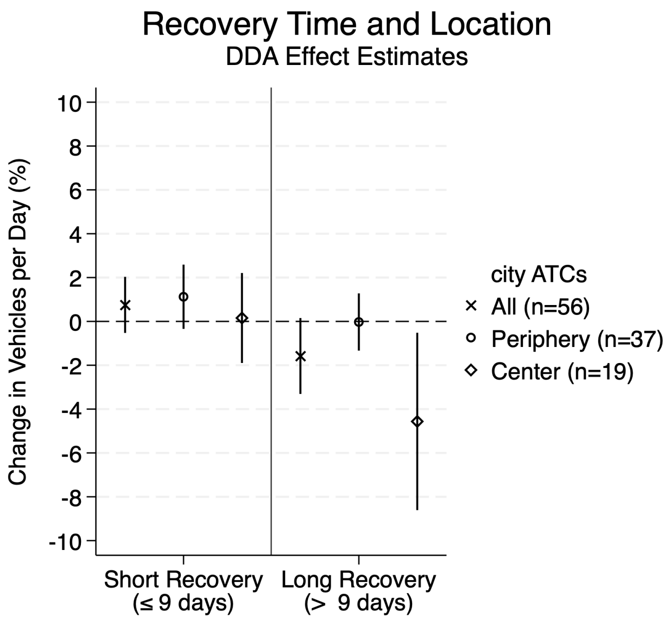

Figure 12: This figure plots don't drive appeal (DDA) effect point estimates by recovery time since the previous DDA event and ATC location. DDA event windows include a total of 277 calendar days for long recovery DDAs and 226 calendar days for short recovery days. Table 8 in appendix C displays corresponding DiD regression estimates.

Finally, figure 12 plots point estimates highlighting differences in DDA effectiveness by between-event recovery time and counter group location.[45] Looking at all ATCs, DDAs reduce traffic in Stuttgart by a statistically significant 1.6% after a long recovery

[45]Table 8 in appendix C shows regression estimates.

period of at least nine days, but do not meaningfully impact traffic levels after a short recovery DDA. In column 1 of table 8 in appendix C, the point estimate on the linear combination of short-recovery DDA terms corresponds to a 0.75% increase in traffic during short-recovery DDAs. We then separately estimate equation 10 for city center and periphery counters. Of the four disaggregated estimates, the DDA effect is only statistically significant for Stuttgart ATCs at the city center after a longer than median recovery time. During DDAs following a shorter than median recovery period, the estimated DDA effect is between +1.1% and +0.2% and statistically insignificant at the 10% significance level for ATCs at both the city periphery and center respectively, providing empirical evidence for hypothesis 3 that an insufficiently long recovery period may hamper overall DDA effectiveness. While the DDA effect remains statistically insignificant and of negligible magnitude (-0.03%) for periphery counters during DDAs following longer recovery periods, the DDA effect increases to over a 4.6% reduction at the city center following a long recovery period and is statistically significant at the 5% level.

These dynamic patterns discussed in this section capture our main theoretical hypotheses from section 3. In figure 10, we show that the DDA leads to traffic reductions that are strongest at the beginning of DDA events and subside over the DDA's duration, as hypothesized social norm effects and other dynamic factors kick in. We show in figure 12 and highlight in our spatially disaggregated analysis that the DDA is most effective in reducing traffic at the city center, in particular following longer between-event recovery periods, confirming our hypothesis that DDA responsiveness is sensitive to recovery time. Finally, our results in figure 11 point to suggestive evidence that individuals trade-off voluntary pollution reductions during the treatment period for pollution increases (i.e. additional car trips) in the posttreatment period.

7 Conclusion

Taken together, our theoretical framework and the results of our empirical test suggest that policy-makers should carefully consider dynamic factors when designing DDA programs and other policies appealing for voluntary pollution mitigation. Our results show that, on average, DDAs decrease traffic on DDA days by less than 1% in line with the program's overall objective. To put this into perspective, this is less than the difference between traffic levels in Stuttgart on an average Monday versus an average Tuesday.[46]

[46]Monday counter-day traffic averages 18,889 vehicles per day and Tuesday 19,232. The difference in mean levels is 1.8%.

We highlight several important caveats to this result. First, the DDA is most effective immediately after it is activated, and we show that it leads to an average reduction of about 3% on the first three DDA days. Second, the DDA is only effective on aggregate following a lengthy between-event recovery period at the city's center. We find that the prediction that DDAs reduce driving on DDA days can be rationalized by appealing to a behaviorally informed model of car owners, and this passes an empirical test.

Our estimated overall DDA effect of about a 1% traffic reduction on DDA days is situated between no effect results from other DDA studies (Noonan, 2014; Sexton, 2012; Cummings and Walker, 2000) and Cutter and Neidell (2009)'s finding of 2%-3% traffic reductions on *Spare the Air* days in San Francisco, USA. Our result contrasts with the finding that Salt Lake City, USA's particulate matter alert inadvertently increases traffic in the city by 3%-4% (Tribby et al., 2013). On aggregate, we believe these modest traffic reductions are not substantial enough to meaningfully impact pollution levels in the policy's target area. However, an analysis of DDA pollution impacts is beyond the scope of this paper. Our analysis also emphasizes that heterogeneity in spatial and temporal effectiveness may be obscured by overall DDA effect estimates.

These findings may generally caution policy-makers interested in combining AQAs with DDAs. This policy bundle has demonstrated mixed effectiveness for achieving driving reductions in other settings, and our study does not provide resounding evidence that this type of policy is persistently effective even when implemented in an ideal setting that has widespread environmental preferences and a dense public transit network. Our analysis is limited to analyzing the impacts of the DDA policy on traffic flows and does not evaluate it relative to other presumably important policy-making factors such as its implementation cost, its impact on residents' perceived quality of life, or its effect on actual pollution exposure. For example, we find suggestive evidence in our analysis that DDAs may displace some traffic to the city periphery. It is not clear in Stuttgart's case whether modest traffic decreases at the city center and traffic increases at the periphery effectively reduce air pollution exposure in the target population. However, policy-makers might value traffic and emissions reductions at the city center, where population density is often highest, more than moderate increases at the periphery. Pollution monitoring systems which provide more spatially resolved pollution measurements would enable a more holistic consideration of spatially-heterogeneous DDA pollution impacts.

The external validity of our results may be limited by Stuttgart's self-selection into the program. Stuttgart authorities designed and implemented the DDA program in response to the city's prolonged non-compliance with EU air quality standards with the ostensible belief that the DDA would lead its motorists to voluntary drive less to reduce pollution peaks.[47] In an ideal experimental setting, we would compare Stuttgart to a city that fully mimics Stuttgart, but authorities in the comparison city do not broadcast a DDA for reasons unrelated to its impact. Given the empirical nature of our analysis, such a perfect counterfactual does not exist – we don't know why Munich never chose to implement a DDA program, but it is likely not random. So, we urge caution when considering whether observed effects will transfer to different cities.

Finally, several other factors which we cannot observe could plausibly affect our estimates. First, we cannot account for same-day traffic shocks at the counter level. While we do not have information about traffic events which may heterogeneously affect car trip demand across counters (e.g. traffic jams, accidents, large events, etc.), barring remarkable changes in traffic conditions on DDA days or considerable spatial displacement effects, we think it is unlikely that same-day traffic shocks differ systematically on treatment days or would otherwise significantly bias our DDA effect estimates. Furthermore, we expect temporary traffic displacement to average out across nearby counters. Second, our analysis is limited to analyzing aggregate traffic impacts and provides little evidence of the individual level mechanisms underlying policy effectiveness. We are unable to observe individual motorists' driving decisions, expectations about DDA effectiveness, or their DDA information exposure (e.g. salience of DDA messaging, consumption of AQA-adjacent programming, etc.). For example, motorists may make their transportation choices based on some combination of weather forecasts, congestion expectations, and beliefs about the DDA, all of which we do not observe. Future research examining individual level responses to DDAs with individual level commuting data and individual level DDA information exposure could provide important insights into which population subgroups are responsive to appeals for voluntary pollution mitigation. Such analyses might also be able to shed light on socioeconomic dimensions of DDA effectiveness and, with an eye to an equitable mobility transition, inform policy-makers about effective targeting approaches and the distributional impacts of their policies.

[47] To our knowledge, Stuttgart is the only city in Germany to have implemented a large-scale program appealing for voluntary driving reductions to temporarily reduce pollution.

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A Replication Package

The data and Stata code used to conduct this analysis is available online at `https://doi.org/10.11588/data/TO3AAL`.

B Additional Tables

Table 4: DDA Activation: Pretreatment and Treatment Days by Day-of-the-Week

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
Pretreatment								
-6+	17	17	14	15	15	17	18	113
-5	4	4	9	4	4	3	2	30
-4	2	4	4	9	4	7	3	33
-3	3	2	4	4	9	5	7	34
Issue	8	5	2	4	6	10	7	42
Bridge	7	8	5	2	4	6	11	43
Total	41	40	38	38	42	48	48	295
Treatment								
1	12	7	8	5	2	4	6	44
2	6	12	7	8	5	2	4	44
3	4	2	9	7	7	3	2	34
4	0	3	2	9	6	5	3	28
5	2	0	3	2	9	4	4	24
6	3	2	0	2	2	6	4	19
7	3	2	1	0	2	1	6	15
8	6	2	1	1	0	1	0	11
9	0	5	2	1	1	0	0	9
10	0	0	3	2	1	0	0	6
11	0	0	0	3	1	1	0	5
12	0	0	0	0	2	0	1	3
13	1	0	0	0	0	2	0	3
14	0	1	0	0	0	0	1	2
15	1	0	1	0	0	0	0	2
16	0	0	0	1	0	0	0	1
Total	38	36	37	41	38	29	31	250

Table 5: DDA Termination: Treatment and Posttreatment Days by Day-of-the-Week

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
Treatment								
-5+	18	15	16	16	12	11	12	100
-4	3	9	4	3	4	4	1	28
-3	1	4	11	4	5	5	4	34
-2	7	1	5	13	4	5	9	44
-1	9	7	1	5	13	4	5	44
Total	38	36	37	41	38	29	31	250
Posttreatment								
0	4	7	7	1	3	12	2	36
1	2	4	7	7	1	3	11	35
2+	19	17	16	22	26	15	15	130
Total	25	28	30	30	30	30	28	201

C Additional Regression Results

Table 6: OLS and DiD Regression Results: Overall DDA Effect (Controls, No Lags)

	(1) OLS b/se	(2) OLS b/se	(3) OLS b/se	(4) OLS b/se	(5) DiD b/se	(6) DiD b/se
DDA Active (=1)	0.0130***	-0.0059*	0.0076***	-0.0074**	0.0114	-0.0132**
	(0.0027)	(0.0033)	(0.0026)	(0.0031)	(0.0076)	(0.0060)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lags	No	No	No	No	No	No
All Days	Yes	No	Yes	No	Yes	No
Time FE	YM	YM	YMxATC	YMxATC	Date	Date
Unit FE	ATC	ATC	ATC	ATC	ATC	ATC
# ATCs	56	56	56	56	76	76
Observations	27,643	12,568	27,634	12,546	39,373	17,622

Note: Dependent variable is logged vehicles per counter-day. Controls include contemporaneous weather and pollution variables. Lags are two days of lagged weather and pollution covariates. Regressions either include all 733 PM season days or 331 non-holiday weekdays excluding DDA transition days. Unit fixed effects are always at the automatic traffic counter level. Time fixed effects are either year-month ("YM"), year-month by ATC ("YMxATC"), or calendar date. Standard errors clustered on counter in parentheses. *=p<0.1, **=p<0.05, ***=p<0.01.

Table 7: OLS and DiD Regression Results: Overall DDA Effect (No Controls, No Lags)

	(1) OLS b/se	(2) OLS b/se	(3) OLS b/se	(4) OLS b/se	(5) DiD b/se	(6) DiD b/se
DDA Active (=1)	0.0721***	0.0055	0.0679***	0.0030	0.0118	-0.0039
	(0.0042)	(0.0041)	(0.0035)	(0.0024)	(0.0084)	(0.0068)
Controls	No	No	No	No	No	No
Lags	No	No	No	No	No	No
All Days	Yes	No	Yes	No	Yes	No
Time FE	YM	YM	YMxATC	YMxATC	Date	Date
Unit FE	ATC	ATC	ATC	ATC	ATC	ATC
# ATCs	56	56	56	56	76	76
Observations	27,673	12,568	27,664	12,546	39,403	17,622

Note: Dependent variable is logged vehicles per counter-day. Controls include contemporaneous weather and pollution variables. Lags are two days of lagged weather and pollution covariates. Regressions either include all 733 PM season days or 331 non-holiday weekdays excluding DDA transition days. Unit fixed effects are always at the automatic traffic counter level. Time fixed effects are either year-month ("YM"), year-month by ATC ("YMxATC"), or calendar date. Standard errors clustered on counter in parentheses. *=p<0.1, **=p<0.05, ***=p<0.01.

Table 8: DiD Regression Results: Recovery Time and Location DDA Effect

	(1) All DiD	(2) Center DiD	(3) Periphery DiD
Main coefficients			
DDA=1 × Treated=1	0.0075	0.0016	0.0112
	(0.0065)	(0.0105)	(0.0075)
Recovery=1 × Treated=1	-0.0024	-0.0215	0.0068
	(0.0089)	(0.0218)	(0.0071)
DDA=1 × Recovery=1 × Treated=1	-0.0209***	-0.0257**	-0.0184**
	(0.0066)	(0.0113)	(0.0078)
Sum of coefficients			
Short Recovery DDA	0.0075	0.0016	0.0112
	(0.0065)	(0.0105)	(0.0075)
Long Recovery DDA	-0.0158*	-0.0456**	-0.0003
	(0.0088)	(0.0206)	(0.0067)
Controls	Yes	Yes	Yes
Lags	Yes	Yes	Yes
Days	503	503	503
DDA Days	227	227	227
Short-Window DDA Days	148	148	148
Long-Window DDA Days	79	79	79
Time FE	Date	Date	Date
Unit FE	ATC	ATC	ATC
# ATCs	75	39	56
Observations	26,832	13,978	20,836

Note: Dependent variable is logged vehicles per counter-day. Controls include contemporaneous weather and pollution variables. Lags are two days of lagged weather and pollution covariates. Regressions include PM season days within the specified window of each DDA activation day. Unit fixed effects are always at the automatic traffic counter level. Time fixed effects are calendar date. Standard errors clustered on counter in parentheses. *=p<0.1, **=p<0.05, ***=p<0.01.

D Additional Graphics

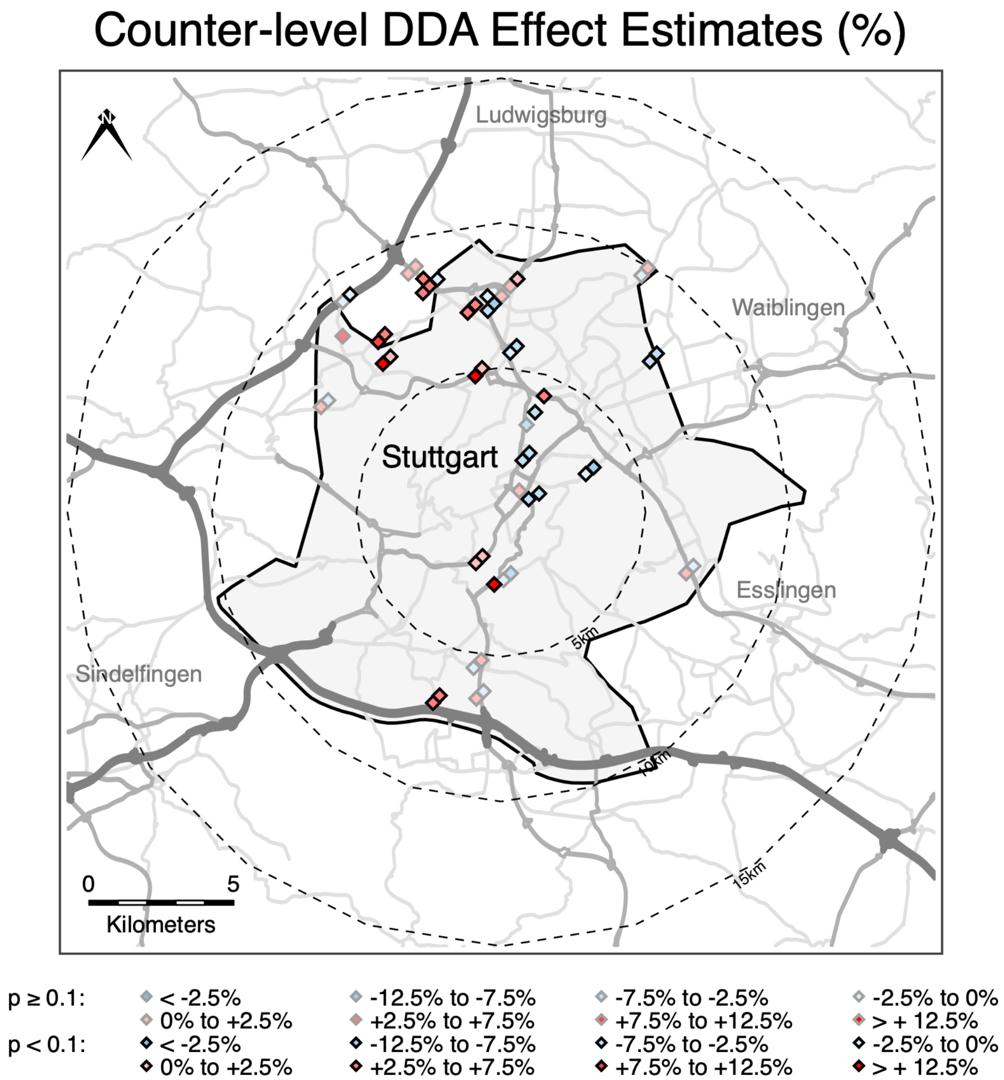

Figure 13: This figure maps counter-level don't drive appeal (DDA) effect point estimates at ATC locations from our main DiD regression model. Marker color corresponds to estimated effect sizes. Counter-level estimates that are statistically significant have a black marker border, while statistically insignificant markers have a grey border. Map includes Stuttgart administrative boundaries, main roads, and buffer zones in five kilometer intervals around the Stuttgart city centroid as in figure 4. Data Sources: OpenStreetMap, IVLZ, BaSt, BKG, and own calculations.