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Behavioural Salience and Environmental Outcomes: Clearing the Air with the Stockholm Congestion Tax

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Abstract: This paper investigates the causal impact of the Stockholm Congestion Tax on hourly NO_2 concentrations over the period 2006 – 2023. I test three hypotheses: (i) whether the seven-month 2006 trial and the 2007 permanent introduction yielded equivalent emissions reductions; (ii) whether the 2016 tariff increase generated a larger decrease in NO_2 emissions than the 2007 – 2015 baseline fee; and (iii) whether peak-period charges produce stronger abatements than off-peak fees of equal magnitude. Upon employing OLS, interrupted time-series (linear and spline-augmented), and event-study models on data from six inner-cordon monitoring stations, and controlling for seasonality, meteorology, and macroeconomic trends, I find that the permanent launch did not replicate the trial's 2.3% reduction but instead coincided with a 1.7% increase in NO_2 emissions. The 2016 fee hike yielded a modest 0.5% decline, while peak-hour surcharges produced a pronounced 4.5% reduction as compared to negligible off-peak effects, confirming H3. These results highlight behavioural salience thresholds and a concave-convex abatement curve that peaks at mid-range tariffs. I conclude that sustained environmental gains require periodic, salient fee adjustments and targeted peak pricing, informing the design of cost-effective congestion pricing mechanisms.

Keywords: Behavioural Economics, Congestion Taxation, Environmental Economics, Greenhouse Gas Emissions, Pigouvian Taxation

JEL: B4, C5, E6, E7, H2, N7, Q5, R4

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1 Introduction

Urban congestion is a persistent challenge in modern cities with significant economic, environmental, and social costs. Traditional responses through modified urban planning, such as road expansion, have proven to be limited in efficacy, which has led to the increasing adoption of congestion pricing policies. While heavily debated, the Pigouvian tax aims to mitigate negative externalities related to road traffic with minimum disruption, often supported by the possibility of seamless integration thanks to rapidly developing automated tolling and GPS technology, with many governments now also coming to view it as an alternative source of revenue to fund further reinvestment into the improvement of their public transportation infrastructure. The first major congestion pricing tax, the Area Licensing Scheme (later converted to an electronic road pricing (ERP) system), was introduced in 1975 in Singapore, and its widely heralded success led to the later adoption of the London Congestion Charge in 2003.

Stockholm is a seminal case study in which congestion taxation was adopted in 2007, after a successful referendum following a seven-month trial period in 2006. Typically, such referendums are met by strong opposition, as seen in Edinburgh in 2005, as Pigouvian taxes are perceived to be unduly burdensome by adding limitations to certain freedoms. Stockholm's success in this matter is likely due to the conscientious timing of the referendum, as well as the low rates of the initial pricing scheme and generally favourable attitude in the Nordics towards sustainability measures. Its success has also led to a similar mechanism being adopted by Gothenburg in 2013.

Beyond just reducing traffic volumes, such policies are also increasingly evaluated for their potential to reduce greenhouse gas (GHG) emissions and mitigate climate change, aligning with broader UN environmental and public health goals as the Paris Agreement deadline approaches. Other common policy instruments targeted at reducing GHG emissions focus on firm-level behaviour, whether it be through carbon pricing (through carbon taxes, emissions trading systems, etc.), subsidies, or regulatory mandates. To this end, congestion taxation policies are some of the few that target individual behaviour and are targeted, dynamic, and revenue positive, with its double dividend model mitigating potential regressivity and building political support – making it attractive to scale and easily transferable.

While congestion pricing is theoretically sound, there is mixed empirical evidence on its long-term environmental effectiveness. Ideally, it should operate as a dynamic form of the Pigouvian tax as road capacity is scarce and varies over time – in rush hour, each extra vehicle slows every other vehicle by more than in other periods, and so, regardless of distance traveled, it is a period of higher emissions. Vickrey's model (1969) states that, therefore, the optimal per-trip toll equals the marginal delay each vehicle inflicts on others, which varies by time and location, as can be seen to be applied in Singapore's ERP system. However, since this is difficult to implement in reality, most governments simply follow the Ramsey intuition (1927) that the price markup over marginal cost is inversely related to the price elasticity of demand – though to varying degrees of success.

In Stockholm, especially, the policy's eventual evolution with two notable price-level increases and the cordon's expansion to Essingeleden in 2016, raises critical questions about its

capacity to deliver sustained welfare benefits while maintaining political legitimacy. Most studies on congestion pricing thus far have been done using traffic flows data, but I have chosen to focus on the outcome directly – NO_2 emissions. As the primary pollutant linked to high temperature congestion in gasoline and diesel engines, it is overwhelmingly linked to motor traffic and has high temporal and spatial responsiveness. Epidemiological studies have also linked exposure to high NO_2 concentrations to respiratory morbidity in children, as well as increased cardiovascular risks - its clearly documented health impact, then, strengthens the real-world justification for congestion pricing as a climate control mechanism. The key concept of Pigouvian taxation is that the socially effective level of activity can be achieved by levying a tax equal to the marginal external cost, to align private incentives with social welfare – this thesis explores whether this level has been met.

1.1 Specific Context

Stockholm's congestion tax incorporated several key technological advancements still at the forefront of their fields today, such as automated tolling (through ANPR technology), which captures license plates at fixed entry and exit points of the relevant congestion zone, thereby minimizing administrative costs and disruption to natural traffic flow patterns. The low-friction nature of this enforcement has been key in maintaining compliance while avoiding the costs of physical toll booths or manual verification. However, unlike Singapore's ERP system, Stockholm has forgone GPS tracking, so it does not differentiate between vehicles passing through a certain number of times versus vehicles circulating within the zone itself, limiting distance-based or time-based pricing opportunities, which raises a few concerns about the equitable nature of the tax.

The zone usage-based charge has been implemented with variable pricing based on time of day, with a maximum cap per vehicle per day applied, so as not to punish drivers too harshly. The tax is applied only on weekdays, between 6:00 – 18:30, excluding public holidays, their eves, and the month of July (excepting the first five weekdays of the month). Limited exemptions are offered for emergency vehicles, mopeds/motorcycles, and buses (taxis, foreign cars, and eco-vehicles were also initially exempted until 2007, 2015, and 2016 respectively). However, there are no income-based discounts, neglecting to directly account for any negative distributional effects. While there is some equity-focused revenue allocation in the form of earmarked funds for transportation infrastructure, this is rather indirect and does not explicitly target any particular subset of beneficiaries.

This pricing structure (*Table 1*) provides an interesting environment to study behavioural patterns as prices are not varied based on any dynamic variables (such as traffic levels, pollution, or demand surges). The transparency and accessibility of its design means that all actions can be taken in the context of full information and so it is likely that we should expect behaviour approaching rationality, a key assumption in typical Pigouvian tax theory to meet the standard of homo economicus.

The initial trial was set from 3rd January to 31st July 2006, with the referendum being held soon after on September 17th. The tax was then permanently implemented on August 1st 2007, after which there have been only two price hikes – one on January 1st 2016, in which it was also announced that the charging cordon would be extended to include Esssingeleden (*Fig. 1*); and one on January 1st 2020, which also saw the introduction of the separation between 'peak season' and 'off-season' pricing schemes, all summarised in Table 1. The overall progression of the timeline reflects both a technical evolution and a shift in public participation from democratic approval to

what can be assumed to be implicit adherence. By examining this evolution more closely, this paper aims to uncover the impact of perception on the effectiveness of a congestion tax.

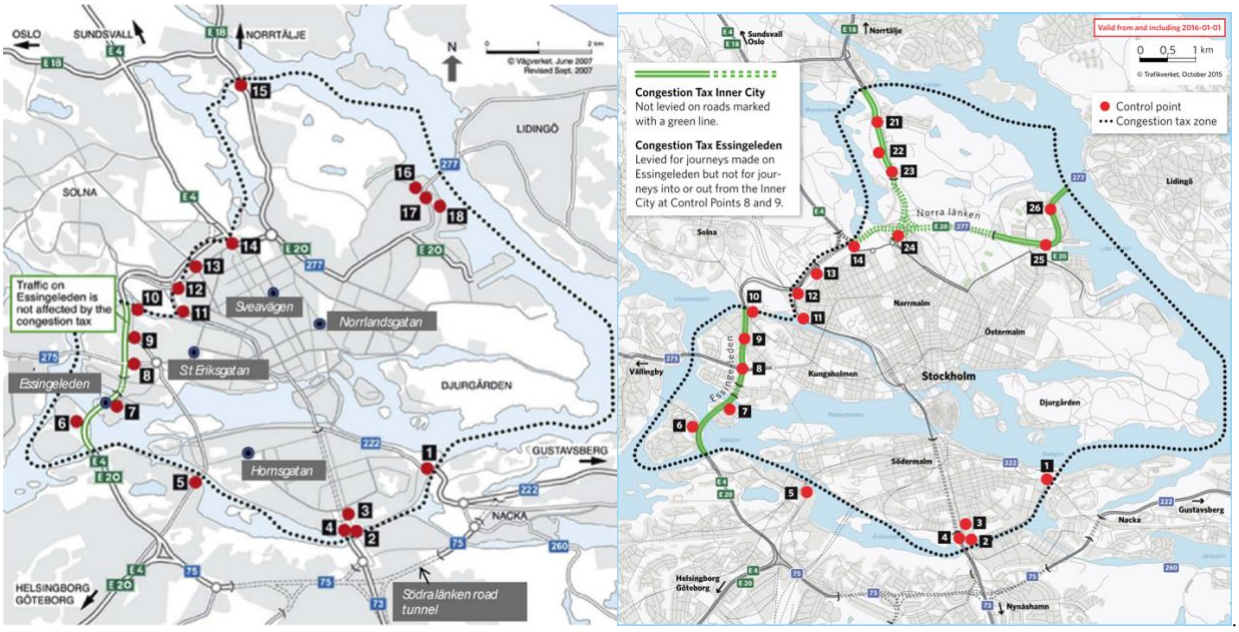
Table 1: Congestion Pricing Mechanism (SEK)

Time Intervals	03-01 – 31-07-2006	01-08-2007	01-01-2016	01-01-2020 (Off-Peak)	01-01-2020 (Peak)
6:00 – 6:29	-	-	-	15	15
6:30 – 6:59	10	10	15	25	30
7:00 – 7:29	15	15	25	35	45
7:30 – 8:29	20	20	35	35	45
8:30 – 8:59	15	15	25	25	30
9:00 – 9:29	10	10	15	15	20
9:30 – 14:59	10	10	11	11	11
15:00 – 15:29	10	10	15	15	20
15:30 – 15:59	15	15	25	25	30
16:00 – 17:29	20	20	35	35	45
17:30 – 17:59	15	15	25	25	30
18:00 – 18:30	10	10	15	15	20
Max/vehicle/day	60	60	105	135	150

Source: Eliasson et al. (2009), Trafikverket, Transportstyrelsen

Figure 2: The Changing Charging Cordon: 2006 – 2015 (1), 2016 – Present (2)

(1) **(2)**



Source: Eliasson et al. (2009), Trafikverket, Transportstyrelsen

2 Literature Review

The literature on congestion pricing is vast and varied. In the following sections, I will outline relevant literature, both theoretical and empirical with regard to my research and highlight how my study contributes to the existing body of work.

2.1 Impacts of Congestion Pricing

Börjesson et al. (2012) explore a comprehensive assessment of the initial impacts of the tax in "The Stockholm Congestion Charges: Five Years On". They found that the trial period led to an initial decrease of 28% in traffic volumes in January, which was maintained if not improved upon over time, proving the high long-run cost elasticity of traffic with limited adverse effects. They also identified secondary benefits such as increased public transport use and improved air quality. The paper also notes that the exemption of alternative-fuel vehicles significantly boosted their sales, and though this allowance has now been revoked, it was a pertinent example of how policy design can inadvertently shape consumer responses. Most of the analysis focused on traffic volume data from 01-2005 to 09-2010 through time series models and cross-section analyses adjusted for external factors, leaving open questions about the persistence of these trends in the long term, which I hope to touch upon in this paper.

2.2 Health Impacts of Air Quality

Johansson et al. (2008) look further into air quality and traffic in “The effects of congestions tax on air quality and health” in Stockholm during the trial and assess changes in NOx and PM10 concentrations compared with corresponding periods in 2003, 2004, 2005 and 2007. Their findings showed significant reductions in both pollutants, with variations due to weather and road conditions, with particularly pronounced effects in central areas. They linked these pollutants to associations with respiratory and cardiovascular diseases and posit on the potential public health benefits of the tax. However, the authors mention to be cautioned about the limitations of their study due to fluctuating meteorological factors (such as an ‘unusually wet’ spring in 2006), motivating a need for longer-term studies across more varied conditions.

Extending upon public health implications of the tax, Simeonova et al. (2018) analyses asthma-related health outcomes in Stockholm for children aged 1-5 in "Congestion Pricing, Air Pollution, and Children's Health". Using a difference-in-differences framework, they find that acute asthma attacks and related hospital visits declined following the introduction of congestion pricing and further link the fact that these health outcomes serve as proxy indicators for reduced pollution exposure, thereby reinforcing the environmental justification of the tax. Like earlier studies, their analysis ended in 2010, and it is uncertain whether the 2016 price hike led to further improvements in outcomes.

More recently beyond Sweden, Bherwani et al. (2020) investigated changes in air pollution and the associated health costs during the quarantine and lockdown period in Wuhan, Delhi, Paris, and London as compared to 2019, in their paper “Valuation of air pollution externalities: comparative assessment of economic damage and emission reduction under COVID-19 lockdown”. Their paper quantifies the economic burden of air pollution-related illnesses and argues that reducing air pollution has positive spillover effects for overall economic productivity in terms of reduced hospital visits and time taken off work. While their natural experiment has

quite a different setting, the paper strengthens the case for the benefits of internalising environmental externalities even when considering increasing economic activity.

2.3 Urban Effects

A common objection to congestion pricing is the perception of an expected negative impact on urban commerce, especially when hindering economic growth is a particularly unfavourable outcome. However, Bent and Singa (2009) suggest otherwise in "Modal Choices and Spending Patterns of Travelers to Downtown San Francisco, California Impacts of Congestion Pricing on Retail Trade", showing that non-driving visitors (classified as transit users and pedestrians) not only formed the majority of downtown visitors, but also tended to spend more than car users. They mention that people surveyed say they would prefer even less congestion in the area, which could mean that implementing congestion pricing would actually lead to more visitors, improving sales. Although their study is focused in San Francisco and not empirically tied to pricing implementation, it offers a counter-narrative to the typical critiques on Pigouvian taxation and its impact on urban economic dynamics.

2.4 Theoretical Frameworks for Pigouvian Taxation

In "A Reformulation Of The Theory Of Optimal Congestion Tax," Else (1981) presents a foundational treatment of optimal congestion taxation in the private and social costs (concerning delays and emissions in particular) of using road transport, where private cost and marginal social costs are initially described to be functions of traffic flow. For each traffic flow, the marginal social cost is found to be higher than the private cost, and so it considers the case of the existence of two equilibriums: one where the demand curve meets the private cost curve, and another where the demand curve meets the social cost curve. Crucially, the social cost already includes the private cost in its estimation, implying the existence of an optimal Pigouvian tax equating to the marginal external cost and aligning private incentives with social welfare at the point at which the demand curve intersects with marginal social cost less private cost. Here, the focus is on costs for all drivers actively exceeding private costs and creating negative externalities through longer driving times. The act of driving on the road is described as adding a car to the total number of vehicles, and so the focus is shifted from the optimum traffic flow to the optimum number of cars, though the underlying discussion of social cost exceeding private cost is a cornerstone in the justification of the implementation of congestion pricing measures in the search for a charge equivalent to this difference.

2.5 The Behavioural Lens

Behavioural extensions to congestion pricing theory are also increasingly significant, as seen in Chetty et al. (2009) in "Salience and Taxation: Theory and Evidence" showing that consumers tend to underreact to taxes when they are not salient, reducing their effectiveness. In the context of Stockholm, the clear and highly visible pricing structure may have enhanced behavioural responsiveness, in addition to the opportunity the public had to consciously opt in to the tax, allowing for greater active engagement in both recognizing the tax (in terms of general awareness) and in appreciating the intention behind it. In this paper, I investigate whether this active knowledge faded over time and if the 2016 price increase was met with the same salience.

Jack S. Levy (1992) further informs this behavioural lens by extending Kahneman and Tversky's concept in "An Introduction to Prospect Theory". The theory's two-stage decision-making model (editing and evaluation) suggests that individuals tend to assess outcomes relative to a reference point. Naturally, drivers would have perceived the 'free' model as the status quo, and the introduction of congestion pricing would have triggered some amount of loss aversion, explaining early resistance. Over time, however, as the tax likely became normalised as active acceptance didn't have to be as conscious of consideration, especially when reinforced by seamless procedural integration and fair payment invoices.

In their work, "Primacy Effects in Justice Judgments: Testing Predictions from Fairness Heuristic Theory," Lind et al. (2001) further explore how people use a perceived sense of 'fairness' as a shortcut to informing their judgments on institutions or policies. Understanding how this dynamic was affected by the very visible price hike in 2016 would be crucial in interpreting the behavioural acceptance of the tax, its perceived environmental benefits, and therefore the overall impact on its potential for sustainability, and would make for an interesting future extension.

3 Hypotheses Development

This paper contributes to environmental economic literature by shifting the focus from traffic flow metrics to a directly climate-relevant outcome: 'Urban-Traffic' NO_2 emissions. Estimating the marginal abatement associated with every additional Swedish krona provides evidence that can inform tariff-setting debates and supply benchmarks for other cities considering higher charges or congestion pricing re-designs.

Empirically, the scope covers six stations within the 2006 cordon using hourly NO_2 emissions data with a common window that spans from 02-01-2006 to 31-12-2023. However, because the sample excludes suburban sites and predates 2006 dynamics, external validity is, necessarily, limited. Moreover, the absence of more high-frequency meteorological controls (weather data) is likely to attenuate the precision of the estimated toll elasticities, which should be borne in mind.

Traditional congestion tax theory posits that once a price is introduced, motorists will re-optimise their schedules, route choice, and mode of transport – subsequent re-imposition of the same schedule should, therefore, add little incremental abatement because the low-cost adaptations have already been exhausted (Small & Verhoef 2019). As discussed above, empirically, early evaluations of the trial period reported around a 25 – 30% fall in traffic, with similar declines to be observed in NOx and PM_{10}. Prospect theory suggests that drivers, once having absorbed the initial 'loss' of paying the fee during the trial period, should feel, upon the permanent implementation of the congestion pricing mechanism, as a reinstatement to a (previous) status quo, muting additional reaction. However, I believe the gap between the trial and the permanent implementation of the tax was sufficiently far apart that the previous status quo might have been forgotten entirely. Accounting for slow habit formation and quick reference-point normalisation, this leads us to my first hypothesis:

H1: Pilot-permanence equivalence: *The seven-month trial in 2006 and the introduction of the permanent congestion pricing mechanism in 2007, produced similar decreases in hourly NO_2 emissions.*

While the presence of a charge should correct some price externality, the magnitude of the price should determine the magnitude of the effect in driving back to the social optimum. Most congestion-demand studies find non-linear price elasticities. Behavioural investigations on tax salience show that prices must cross a certain threshold before they have a meaningful impact. I expect smaller fees to be more likely to alter scheduling choices, and that steeper tolls are often required to trigger a mode shift, the latter of which can be captured in NO_2 emissions data. To this end, I present my second hypothesis:

H2: Tariff magnitude effect: *The 2016 tariff increase generated a larger reduction in NO_2 than the baseline charge in place between 2007 and 2015.*

In a similar vein, empirical evidence from Singapore's ERP shows that peak-hour surcharges concentrate behavioural response into the charged hours, with minimal spillover to other times. In Stockholm, the tariff is around five times higher in the peak hours, creating a strong price gradient. I must also consider the aspects of comfort, convenience, and the requirement of punctuality as key factors in every potential driver's thought process – aspects which are likely prioritised to a greater extent by those who are, in fact, car owners. However, when coupling the extremely high prices with the possibility of greater schedule flexibility for commuters outside the peak hours (seeing as rush hours are termed so due to the set work schedules), the theory of marginal cost pricing leads us to the third hypothesis:

H3: Peak-period dominance: *The NO_2 reduction effect of the charge is stronger during peak-priced hours as compared to off-peak hours.*

4 Data Sources and Variable Definitions

In the following section, I will describe the data used in my thesis, its retrieval, and the constraints applied to the data collection with regard to the research scope. Summary statistics are available in Appendix A.

4.1 Main Data Sources

Hourly toll pricing data for the period 2006-07 to 2016 was retrieved from Eliasson et al. (2009), in their paper "The Stockholm congestion – charging trial 2006: Overview of effects". Toll rates after the first price hike in 2016 were obtained from Trafikverket's (Swedish Transport Administration) official announcement in collaboration with Transportstyrelsen (Swedish Transport Agency), published as an 'ODR Information to the General Public'. The hourly toll rates reflecting the most recent price hike in 2020 were sourced directly from the Transportstyrelsen website.

All NO_2 emissions data come directly from Sveriges Meteorologiska och Hydrologiska Institut's (Swedish Meteorological and Hydrological Institute, SMHI) Datavärdskap luft (Air Data Host) server at an hourly frequency. To ensure consistency among the datasets used, further precautions have been taken to ensure that all NO_2 emissions data used were classified under the 'Urban' area category at the 'Traffic' level. Accounting for this stricter definition of traffic-related emissions and the required of granularity, I pare down the total 21 stations tracked in Stockholm

County to the following six: Lilla Essingen, Hornsgatan 108 Gata, Hornsgatan 85 Gatuniva Norrlandsgatan 29, Sveavägen 59 Gata, Sveavägen 88 Gata. Most of these stations are centrally located and thus enable more focused analysis beyond the presumably unavoidable peaks associated with the morning and evening rush-hour commutes to provide robust insights into overall city mobility dynamics.

4.2 Macroeconomic Indicators

Both population and GDP growth figures have been employed as control variables throughout this paper, and were sourced from the Statistikmyndigheten (SCB) website. While numerous GDP measures were available, I selected this series as it represented real GDP due to its inflation-adjusted nature, allowing us to capture genuine economic growth or contraction while remaining unaffected by price-level fluctuations. More specifically, population data was obtained from the 'Population per month by region, age and sex. Year 2000M01 – 2024M12' database, and GDP growth data was retrieved from the 'National accounts, GDP (ESA2010), change in volume. Quarter 1993K1-2024K4' database.

4.3 Vehicle Operating Cost Controls

The data in the composite car cost file is all collected on a monthly basis from SCB, and has been formulated on the basis of Else, 1981. Here are the 12 cost categories I have chosen to capture: bensin 95 oktan (cost of 95-octane petrol), bensin 98 oktan (cost of 98-octane petrol), bildäck (tyre replacement cost), bilförsäkring (insurance cost), biltillbehör (accessories), biltvätt (car wash), dieselolja (diesel fuel), garagekostnad (garage/storage costs), kontrollbesiktning (periodic technical inspection), körskoleutbildning (driving-school training), parkeringsavgifter (parking fees), underhållsservice (maintenance/service).

The study incorporates this car cost series as a time-varying control dataset because the generalised cost of motoring is widely considered a first-order determinant of travel demand. Here, I take my logic from Else (1981). While car-ownership statistics capture the stock of potential drivers, they are comparatively inert and therefore less informative about the intensive margin – the decision to undertake an additional trip on any given day. By contrast, operating costs respond quickly to market conditions and provide a more precise proxy for the probability that a vehicle owned is actually used. Fuel expenditures dominate both the visibility and volatility of driving costs. In Sweden, retail gasoline and diesel prices are highly responsive to global oil markets and domestic excise taxes, and are assumed to be key factors in deciding between the use of public or private transport. Controlling for these fluctuations allows the analysis to disentangle tax-induced behavioural changes from broad price shocks that would otherwise confound the toll effect.

Maintenance and service costs introduce a second channel of variability as the harsh Nordic winters accelerate wear on tyres, brake systems, and undercarriages, pushing up seasonal outlays for repairs. These expenses track not only physical depreciation and perhaps lower willingness to drive, but also broader inflation in the automotive-service sector, which can influence medium-term mobility decisions. Insurance premiums and statutory fees, though less volatile than fuel prices, still enter the full cost calculation borne by drivers. The index also implicitly captures prevailing financing conditions such as interest rates and credit availability that affect leasing choices and, by extension, kilometer exposure over time. By modelling this composite cost index, the regression framework controls for both random fuel shocks and slower-moving cost

components to attempt to isolate the pure impact of congestion pricing on emissions and traffic volumes.

4.4 Meteorological Controls

Wind speed data is obtained from the Swedish National Institute of Health on SMHI's platform. In the cordoned area, there is only one available monitor: Stockholm-Observatoriekullen A (98230). Wind speed is measured as an average value over ten minutes every three hours and is measured in m/s. Data was available from a timespan of 01-01-1969 to 31-10-2019, with only 158 out of 64669 observations flagged by SMHI as 'Yellow' (suspicious, aggregated, roughly checked archive data, and unchecked real-time data) in the segment of years I used for my dataset. I then resampled this to hourly data to fit the granularity of my main dataset.

5 Research Design

In this section I describe in greater detail how every dataset was handled and explain the logic behind the specific methodologies and approaches used for each statistical technique applied in this paper. Any additional visualisations in this section can be found under Appendix B.

5.1 Data Handling

As the emissions dataset is recorded at an hourly resolution, I resample the congestion tax rates reported in *Table 1* to the same frequency, generating four distinct hourly tariff schedules, each aligned with its respective regulatory period.

Upon retrieving data from six stations in Stockholm County, I found no indication of any potential anomalies at ± 3.5 standard deviations as chosen upon visual inspection (*Fig. B.1).* To obtain an initial indication of data quality, I quantified both the absolute and percentage number of missing observations (*Table B.1)*. At a finer granularity, I extracted hour of day data and then assessed group-level missingness, both by date and by hour (*Table B.2 and Fig. B.2* respectively) to assess whether missingness was systematic or random, and select an appropriate treatment strategy. With the exception of Sveavägen 88 (df6), overall missingness was quite low: no other station lost more than around 4% of their hourly readings although there were a few extended gaps detected, corresponding to multi-hour instrument down time and calibration events. All stations exhibited a similar temporal pattern with slightly higher missingness in the early morning hours (roughly 1:00 – 6:00). However, on an aggregate, missingness counts were roughly even and random. Since df6 displayed substantially higher missingness with extended gaps during key intervention periods, I have chosen to apply a statistically rigorous imputation procedure and flag all extended gaps for all datasets. This consideration also informed my decision to prioritise insights from individual stations' analysis rather than placing greater emphasis on the aggregate dataset.

The data-cleaning and imputation pipeline was implemented in five sequential stages:

(i) Removal of days lacking all NO_2 observations, after which the remaining dataset was visually inspected with particular attention to data availability around key intervention periods.

(ii) Local neighbour mean imputation in which isolated single-hour gaps between two valid readings were filled using the arithmetic average of the preceding and succeeding observations to preserve the local hourly trend and align with the hourly toll-rate structure.
(iii) Extended gap imputation in which they were interpolated with a four-week rolling mean specific to each timestamp to preserve both seasonal drift, hour-of-day profile, and align with the hourly toll-rate structure with a day-mean fall back.
(iv) Final sweep for immediate neighbour missingness, after which the fully imputed station-level series were re-merged into a common, complete dataset spanning the common observation window: df0_final_imputed (*Table 2*).
(v) Sensitivity check using three-week and four-week overlays.

Table 2: Common Time Windows

Dataset	Start	End
df0_final_imputed (Aggregate)	2006-01-02	2017-12-31
df1_final_imputed (Lilla Essingen)	2006-01-02	2023-12-31
df2_final_imputed (Hornsgatan 108)	1999-01-02	2023-12-31
df3_final_imputed (Hornsgatan 85)	2006-01-02	2020-04-17
df4_final_imputed (Norrlandsgatan 29)	2006-01-02	2017-12-31
df5_final_imputed (Sveavägen 59)	1999-01-02	2023-12-31
df6_final_imputed (Sveavägen 88)	2006-01-02	2023-12-31

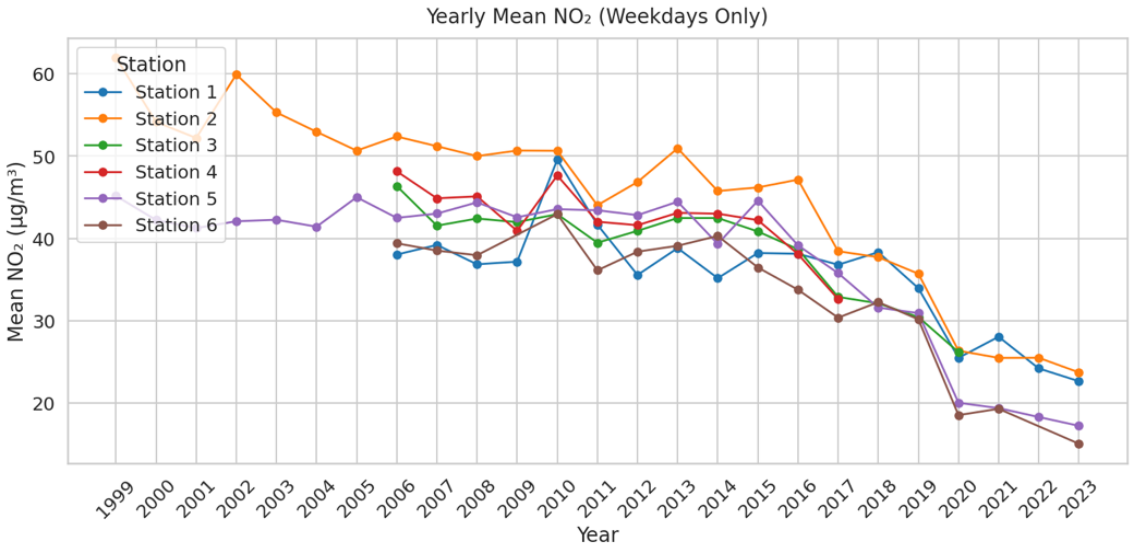
Source: Author's construction

Across all stations on average, daily NO_2 values typically range between 20–30 μg/m³, and so the mean differences of around ±0.005 μg/m³ remain negligible. Dispersion is also similarly low, with all stations exhibiting standard deviations below 0.5 μg/m³. Across the six stations, two-week vs four-week has a higher average mean and variability, as expected (0.00017 μg/m³ and 0.2925 μg/m³ respectively, as compared to 0.00000 μg/m³, and 0.1495 μg/m³ respectively). This can be inspected in greater detail in *Table B.3*. I then constructed Bland-Altman plots (*Fig. B.3*) to determine whether differing aggregation windows introduced systematic bias. I observed that the mean difference remained mostly near zero and that the limits of agreement (±1.96σ) remained tight at roughly ±1 μg/m³, indicating no proportional bias. Although these results suggested that the window lengths were interchangeable, I retained the four-week rolling average to preserve the monthly temporal structure. Scatterplots further corroborated these findings with points tightly clustered along the 45° line and annual means hovering near zero with uniformly narrow interquartile ranges, with only a few outliers in the earlier years. Importantly, this reassured us of a lack of discontinuity around the key policy intervention dates, underscoring the temporal stability of the measurement approach despite the raw data's initially suspicious patterns of missingness. This stability bolsters the internal validity of my quasi-experimental design by ensuring that at least the majority of the year-to-year shift in emission concentrations reflects genuine environmental effects.

The initial visual inspection of the data revealed several macro-level patterns that guided my choice of statistical methodology. Winter-summer seasonality cycles are particularly evident, with sharp winter maxima and summer minima gradually following a downward drift over time. Winter 2007 peaks are appreciably lower than those of winter 2006, a clear step change coinciding with the key permanent implementation policy milestone. Similarly, the 2016 summer troughs reach record lows, and the 2016-17 winter period displays a distinctly compressed spike amplitude. There is also substantial station-level heterogeneity, with maxima and minima declining at

different rates and magnitudes across sites, motivating my use of fixed-effects models to account for this variation.

Figure 2: Time Series Plot of Mean NO_2 Emissions per Station



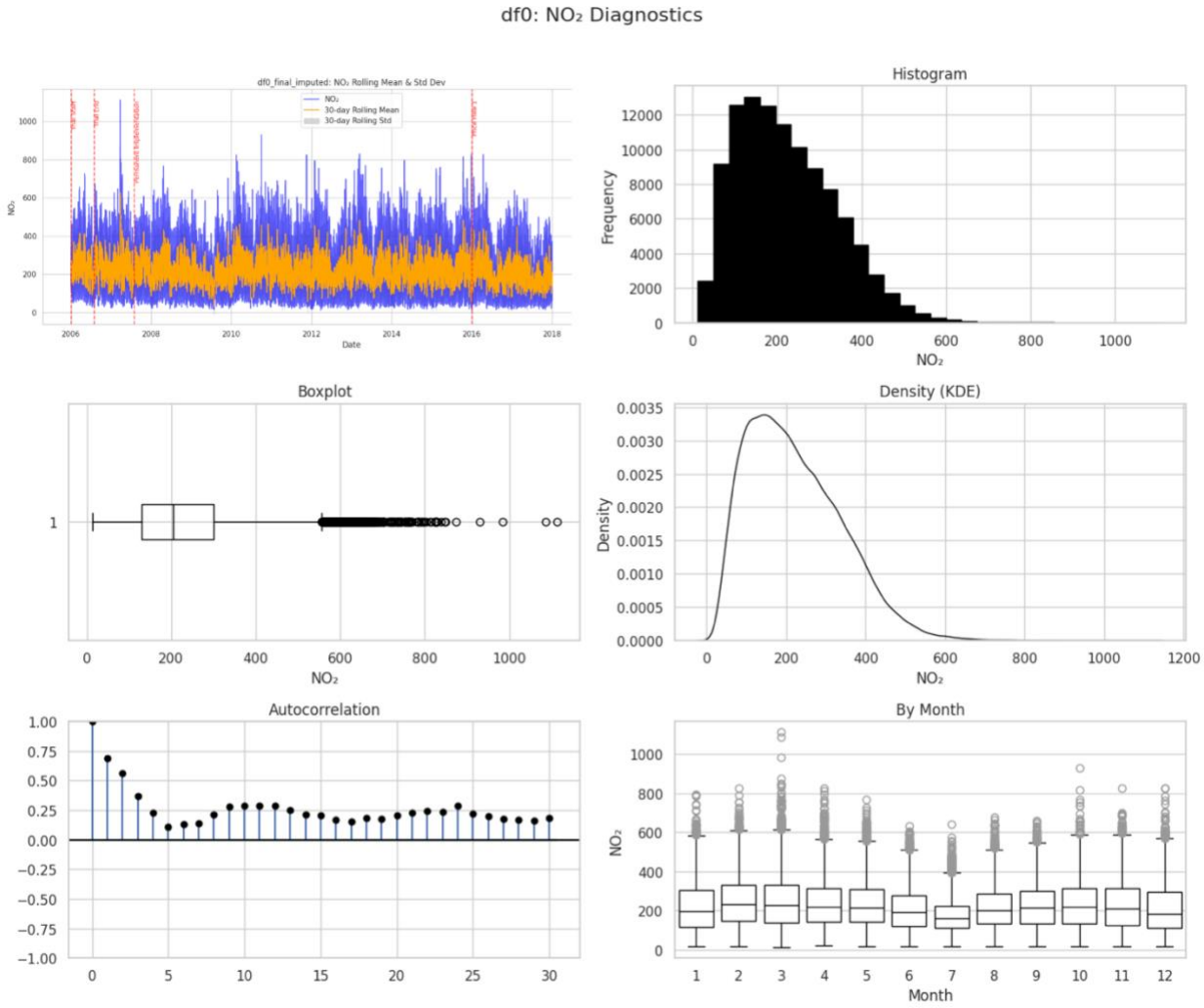
Source: Author's construction

At the annual level, I plotted the mean series (*Fig. 2*), revealing a modest uptick at a few stations in 2006-07, followed by a clear decline after 2007, and a smaller downward shift around 2016. There is a pronounced drop in 2020, with only a partial rebound thereafter, setting a new low baseline. As Sweden imposed comparatively mild pandemic restrictions, despite the significant contribution the COVID-19 pandemic no doubt had on hindering mobility and daily activity, I can likely attribute some of this discontinuity to the concurrent increase in toll rates; to control for this, COVID is taken as a dummy in all regressions in this paper.

In regard to control variables, quarterly real-GDP growth has been interpolated to match the temporal resolution of each model (I have employed forward filling in this case, so as to remain conservative in my assumptions). Monthly population figures for men and women were combined to create two datasets: total population, and total population over 15, which were then compared to assess their suitability. Neither variable suffered from multicollinearity (VIF < 5), but total population over 15 had a markedly lower Akaike Information Criterion (AIC) by around 12, and improved model fit according to the formal nested-F test (ANOVA) that confirmed that it significantly boosted explanatory power ($F = 13.77$, $p = 0.00021$).

5.2 Exploratory Data Analysis

Figure 3: Aggregate Summary Plots



Note: Similar plots for each individual station can be found summarised in *Figure B.4*.

Source: Author's construction

Time Series Plots

The graphs in *Fig. 3* reveal a long-run downward trend in NO_2 emissions from the mid-2000s through 2023, punctuated with a few spikes and troughs. This is broadly consistent with several structural changes as a result of broad, sustained policy efforts, such as successive Euro vehicle-emissions standards, the expansion and increased accessibility of public transport, and a wider change in attitude toward conscious efforts to live sustainably. A 12-month rolling mean reveals a steady decline beginning shortly after 2007, which plateaus around 2010-2015, followed by a sharper descent around the 2016 price hike and a steep decline in early 2020 that persists through 2023.

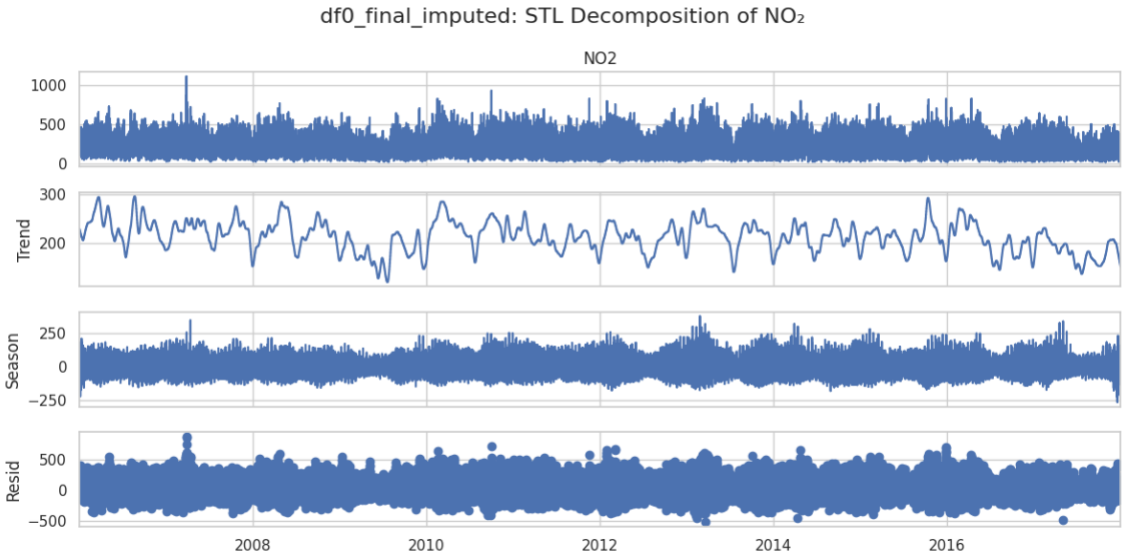
Histograms
The frequency distribution exhibited has quite a pronounced right-skew, with most hourly observations clustered at low-to-moderate concentrations, with a long tail of higher NO_2 emissions. This non-normal distribution violates classical OLS assumptions and motivates much of the variance-stabilising transformations I pursue henceforth. From a policy standpoint, though, these tail events are likely those disproportionately associated with acute health costs, and while a few governments are actively looking into creating a moving target of a toll after a certain threshold has been hit, it has proven difficult to implement in practice.

Box-and-Whisker Plots
On a station-by-station basis, the median hourly concentrations are around 20–30 $\mu g/m^3$ with interquartile ranges (IQR) of 10–50 $\mu g/m^3$, though there are numerous outliers exceeding the upper whisker. I have chosen, however, not to discard 'outliers' (via winsorizing or quantile regression) after a few conversations with Transportstyrelsen and SMHI staff who believe the NO_2 emissions data to be accurate to the best of their ability. As expected, at the aggregate levels, the distribution is less skewed and has a shorter tail as extreme spikes and troughs get averaged in favour of a tighter focus.

Density Plots
These highlight, again, the modal structure with a single dominant mode around 20–40 $\mu g/m^3$ for individual stations with a smooth decay into the right tail; their consistency across stations reinforces the representativeness of the monitoring network.

Autocorrelation Diagnostics
This function reveals a strong persistence where first-order correlations approach 0.9 at the hourly level and 0.6 at the daily level, with visible weekly (lag = 5-7) and annual (lag = 12) cycles. These patterns warrant models accommodating for serial dependence with AR terms, cluster-robust or Newey-West errors, and, where appropriate, seasonal components. The gradual decay implies that shocks are not quickly dissipated, building an expectation that policy interventions manifest in protracted concentration shifts rather than immediate step changes.

Figure 4: STL Decomposition of Aggregate Series



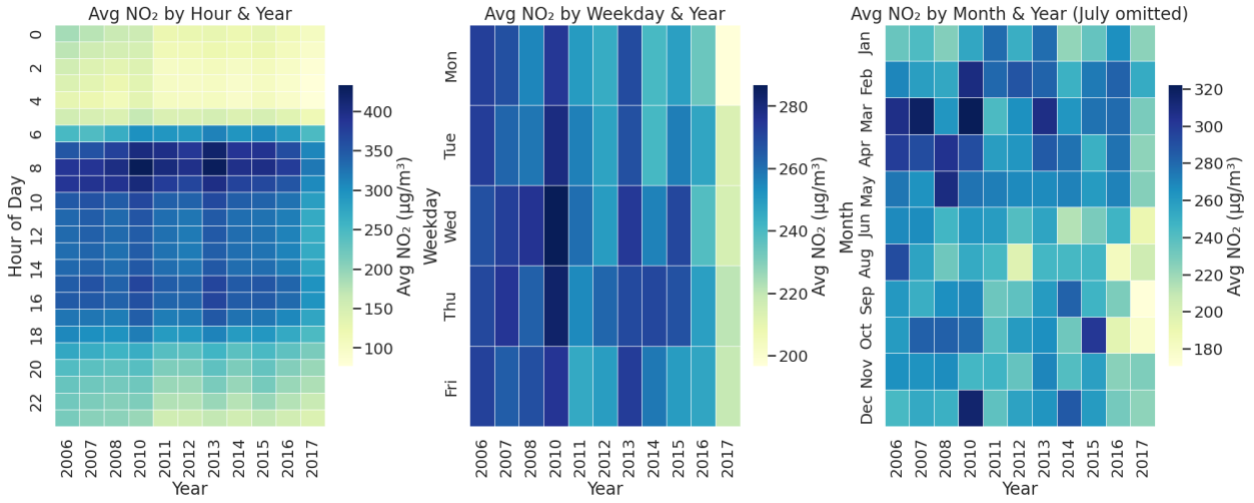
Source: Author's construction

Seasonal Decomposition

The trend, seasonal, and residual components (*Fig. 4*) reaffirm the necessity to control for seasonality as it isolates a recurring winter maximum and summer minimum, likely reflecting season-typical heating demands and temperature-dependent photochemical processes. Monthly aggregates further corroborate this seasonality with January – February displaying the highest medians and widest IQRs and vice versa for July – August, likely due to a traffic lull on account of the summer holidays. Once seasonal cycles are removed, however, residual autocorrelation falls markedly, indicating that most persistence is seasonal rather than stochastic. While a 3-year rolling mean gives a smooth climate trend and variability band, annual aggregation is too coarse for further meaningful analysis, especially when considering most datasets only have around 11 years of data.

Figure 5: Calendar Heatmaps by Hour (1), Weekday (2), and Month (3)

(1) **(2)** **(3)**



Note: I have chosen to exclude 2009 from this visualisation, due to the lack of reliable data from Sveavägen 88 Gata.
Source: Author's construction

Calendar Heatmaps

Fig. 5 reaffirms that there are greater emissions concentrations during weekdays, and, upon aligning with key policy intervention dates, I see that there is no immediate step-change after the permanent implementation of the congestion tax in 2007 and that the emission trajectory lightens only gradually thereafter. In contrast, the 2016 price hike appears to correspond with a distinct reduction in high-concentration days, particularly in winter, consistent with the price-salience hypothesis. There is a clear diurnal double-spike as concentrations surge between 06:00 – 09:00 and again at 15:00 – 18:00, matching commuter peaks, confirming that traffic is the primary driver of hourly NO_2. Weekday patterns validate the choice of weekday fixed effects in the following regressions, with lower levels on Friday likely pointing towards flexible work or early departures. The uniform post-2016 drop across all weekdays underlines that it is the tariff hike, and not an idiosyncratic weekday effect, that drove the improvement. There is evidence that winter peaks diminish over the sample, showing that it is likely the winter months when dispersion is poorest that benefits most from the policy, giving the congestion charge a disproportionate public-health payoff, though I cannot discount the fact that overall traffic flow is also likely impacted solely due to the nature of the season in the Nordics. It is also clear to see here how the higher congestion charge slowly eats away at NO_2 emissions during peak hours, whereas a similar pattern is not immediately evident for other off-peak hours included in the congestion pricing mechanism, consistent with the peak-period dominance.

6 Empirical Methodology

In this section, I present the empirical strategy and methodology used. First I motivate my choice of model, and then I describe a few key features in its construction.

6.1 OLS Regression

Building on my exploratory data analysis, I designed an OLS framework to directly address the principal threats to validity (right-skew, autocorrelation, seasonality, heteroskedasticity), while retaining sufficient granularity to capture the causal signal of congestion pricing. All regressions in this paper are fitted with a COVID dummy to ensure that the non-normal behaviour during the pandemic doesn't go unaccounted for. I consider COVID-19 to have started impacting results on March 11th, 2020 – when the WHO officially declared it a pandemic and when Sweden began imposing large-scale social distancing measures; February 9th, 2022 is taken as the end of the COVID-19 impact on NO_2 emissions as it is the date when Sweden formally lifted most of their remaining national COVID restrictions.

In all regressions run in this study, the dependent variable is: $Y_{it} = \log(NO_{2,it} + 1)$, where i indexes for station and t indexes hour.

This OLS regression is my baseline specification on the appropriately filtered dataset, with station fixed effects, macro controls, meteorological controls, car-cost controls, and Fourier applied beforehand:

$$
\begin{aligned}
Y_{it} = \alpha + \beta_{lag} Y_{i,t-1} + +\beta_t toll_{it} + \sum_{k=1}^{K} \beta_{c,k}\, car_{k,it} + \beta_g GDPgrowth_{qt(i,t)} + \beta_p PopOver15_{mt(i,t)} \\
+ \beta_w windspeed_{it} + \theta 1\{COVIDperiod\} + \sum_{k=1}^{3} \left[\alpha_k \sin\left(\frac{2\pi hT}{24}\right) + \alpha_k^{'} \cos\left(\frac{2\pi hT}{24}\right)\right] \\
+ \sum_{k=1}^{2} \left[\gamma_k \sin\left(\frac{2\pi hT}{365.25 \times 24}\right) + \gamma_k^{'} \cos\left(\frac{2\pi hT}{365.25 \times 24}\right)\right] + C(hour) + C(weekday) \\
+ C(month) + C(quarter) + C(season) + C(station) + \varepsilon_{it}
\end{aligned}
$$

6.1.1 Sample Construction

I work directly with the fully imputed hourly series and only retain times when the congestion charge is applicable: weekdays, excluding Swedish public holidays and their eves and July (except the first five weekdays of July) – the standard temporal filter used in the entirety of this study. This follows the current logic of the application of the congestion charge, and I assume it has been a constant structure since its implementation. Here I construct a function to calculate the hourly toll rate depending on the year (to account for the price hikes in 2016 and 2020), and, for 2020 I add two schedules to capture both off/peak charging structure. Quarterly real-GDP growth and monthly population over 15 are merged and appropriately forward-filled to align with the frequency of the dependent variable. I also add my 'car cost' sub-components and wind speed control to act as non-policy covariates to absorb any other cost shocks that might influence traffic flows, and therefore emissions.

6.1.2 Addressing Distributional and Dynamic Issues

To purge any recurrent temporal patterns that could confound policy effects, I layer the following deterministic controls:

(i) Diurnal cycle: hour-of-day and day-of-week dummies
(ii) Broader seasonality: month, quarter, and meteorological season dummies
(iii) Fourier terms: sine/cosine pairs of order 3 (daily) and 2 (annual), to let the model flexibly fit the 24-hour and annual cycle without over-parametrising, capturing the main harmonics identified in the periodograms.

I pursue log transformation by taking the natural log of the NO_2 emissions to mitigate right-skew, stabilise variance, and down-weight extreme spikes that could otherwise bias the data unduly. I then include a one-period lag of the dependent variable to absorb the strong first-order persistence and soak up inertia. In terms of ensuring robust standard errors, hourly models adopt cluster-robust errors at the daily level, accommodating for intra-day correlation and heteroskedasticity. Coarser aggregated models employ Newey-West heteroskedasticity-and-autocorrelation-consistent (HAC) estimators instead. Before estimation, rows containing missing lags or covariates are dropped, preventing Patsy from silently misaligning the design matrix to avoid desynchronising the clustering vector.

6.2 Interrupted Time Series

To isolate the causal impact of the congestion pricing, I implement an ITS design that explicitly models both level shifts and slope changes while controlling for station heterogeneity, seasonality, and seasonal dependence. The ITS framework complements the structural break analysis by decomposing each effect into an immediate jump and a post-intervention drift, providing a quasi-experimental lens through which any observed NO_2 emissions decline can be more credibly attributed to the congestion charging policy rather than any concurrent meteorological or economic shocks.

Seasonality is a core feature of the time-series model - here I show how I approach the creation of step dummies and post-time dummies:

$$
\begin{aligned}
Y_{it} = \alpha + \beta_{lag} Y_{i,t-1} + \beta_t toll_{it} + \sum_{k=1}^{K} \beta_{c,k}\, car_{k,it} + \beta_w windspeed_{it} + \beta_g GDPgrowth_{qt(i,t)} \\
+ \beta_p PopOver15_{mt(i,t)} + \sum_{b \in trialstart,\ldots,pricehike_2} [\delta_b 1\{t \geq \tau_b\} + \gamma_b (t - \tau_b) 1\{t \geq \tau_b\}] \\
+ \theta 1\{COVIDperiod\} + \sum_{k=1}^{2} \left[\phi_{1h} \sin\left(\frac{2\pi h T}{7 \times 24}\right) + \phi_{2h} \cos\left(\frac{2\pi h T}{7 \times 24}\right) \right] \\
+ \sum_{k=1}^{2} \left[\psi_{1h} \sin\left(\frac{2\pi h T}{365.25 \times 24}\right) + \psi_{2h} \cos\left(\frac{2\pi h T}{365.25 \times 24}\right) \right] + C(hour) + C(station) \\
+ \varepsilon_{it}
\end{aligned}
$$

Where T is time in hours since start, and τ_b are the break-hours.

6.2.1 Panel Assembly

First, I stack the hourly data for all six stations via concatenation into a single panel, which is then indexed by a station identifier so as to absorb time-invariant station heterogeneity. As I did in the OLS regression, I retain only toll-eligible times and unify the datetime index to allow for the computation of toll rates and the alignment of external shocks. I then proceed to treat the controls identically to the OLS regression and then log-transform the NO_2 concentration and continuous covariates to stabilise variance and allow for the interpretation of coefficients as elasticities. A one-hour lag of the dependent variable is also applied and serves to capture the first-order persistence.

Fourier terms are incorporated via smooth sine/cosine pairs to model the dominant weekly (order 1) and annual (order 2) harmonics, to let us flexibly approximate the smooth seasonal swings without too many dummy variables.

Upon defining each policy milestone, I then create:

(i) A step dummy (0: prior to the intervention, 1 thereafter), to estimate any immediate level change;
(ii) A post-slope term to capture any shift in trend following the intervention;
(iii) A station fixed effect variable to absorb any persistent inter-station heterogeneity.

The model is estimated by OLS with Newey-West HAC(24) standard errors as supported by the Durbin-Watson diagnostic to guard against any residual autocorrelation up to the length of a full diurnal cycle. In this case, I chose to avoid heterogenous effects testing since I did not believe that it was worth losing degrees of freedom and risking multicollinearity, especially since I already include station fixed effects and all stations are located rather centrally.

6.2.2 Addressing Rush-Hour Confounding with Spline

To explore potential non-linearities in the toll-emissions relationship, I replace the single 'toll-rate' regressor with a flexible cubic B-spline with seven degrees of freedom, omitting the intercept since the overall constant in the regression already captures the baseline level. Operationally, this expands the scalar toll variable into mutually orthogonal basis functions. This linear combination approximates a smooth 'dose-response' curve over the support of the observed tariffs.

For spline-ITS, I do the same as (2), except I replace the linear toll term $\beta_t toll_{it}$ with a cubic spline in toll:

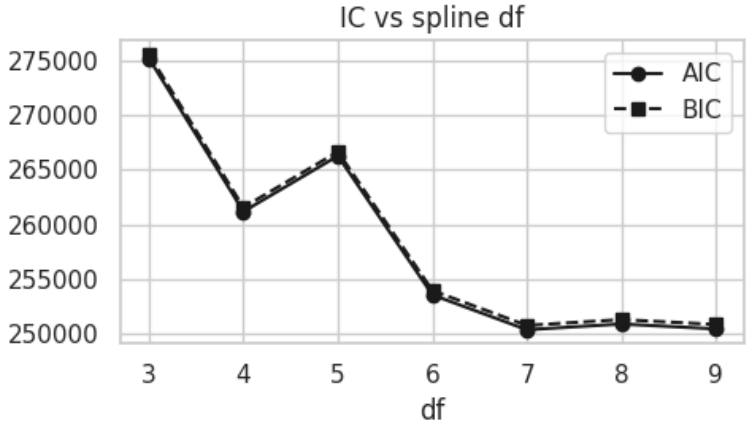
$$Y_{it} = \alpha + \beta_{lag} Y_{i,t-1} + f(toll_{it}) + [same\ controls\ as\ ITS\ above] + \varepsilon_{it}$$

Where $f(x) = \sum_{j=1}^{d} \beta_{s,j} B_j(x)$ is a cubic B-spline with d basis functions, of which I tried $d = 4, 6, 7$.

In the construction of the spline, the vector of hourly toll rates is transformed into a stations × time × basis functions matrix, and knot placement follows Harrell's recommended percentiles

to ensure data-driven flexibility while limiting over-fitting. The spline terms are then integrated back into the ITS structure's stacked panel alongside the previously defined regressors and controls and estimation proceeds via OLS with Newey-West HAC(24) standard errors to preserve comparability with the linear ITS baseline. I proceed to choose the degree of freedom guided by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as seen below in *Fig. 6*. Both AIC and BIC test for balancing goodness of fit against model complexity, with lower values indicating a better trade-off, and both reach a similar conclusion: df = 7 is the best choice, especially since there appears to be a slight increase at df = 8 before it settles down again.

Figure 6: AIC/BIC for Spline



Source: Author's empirical results

In order to visualise the partial effect, I create a grid of toll values in which, for each grid point, the spline basis is evaluated and other regressors are set to their sample means while all policy dummies are zeroed. Multiplying by the estimated coefficients then yields a smooth curve of the ceteris paribus change in log-NO_2 across the tariff range. The non-parametric shape would allow policy makers to identify tariff bands that deliver the greatest pollution benefit per SEK, rather than assuming a constant semi-elasticity.

6.3 Event Study

While the spline augmented ITS captures the average toll response over the full sample, it does not reveal how emissions evolve immediately before and after each intervention. The event study informed by the spline analysis, therefore, complements the main specifications, allowing visual inspection of pre-trends, impact timing, and rebound dynamics.

For each policy shock, observations are restricted to a ±4-week window at hourly granularity centered on the intervention date, creating one dummy per event hour. I compute hour-since-event and build one dummy per hour offset. Then I add station fixed effects to strip out time-invariant station heterogeneity and apply lagged NO_2 to absorb short-run persistence while the prevailing toll rate controls for hour-specific price variation. The control vector includes Fourier seasonality, GDP growth, and population over 15. The ITS step and slope dummies are also included as background controls. The estimation uses OLS with cluster-robust standard errors

(cluster = station), allowing each station its own autocorrelation structure. The stacked design matrix (X) and outcome vector (y) are concatenated across all shocks, after which missing rows are dropped. Coefficients and 95% confidence intervals are plotted against w to yield an event study curve, allowing us to study the parallel trend assumption, impact timing, and cross-validation as compared to the spline-augmented ITS.

For each break date τ, I run:

$$
\begin{aligned}
Y_{it} = \alpha + & \sum_{h=-H,\, h\neq 0}^{H} \gamma_h \, 1\{t - \tau = h\} + \beta_{lag} Y_{i,t-1} + \sum_{j=1}^{7} \beta_{s,j} \, B_j(toll_{it}) + \beta_w windspeed_{it} \\
& + \beta_g GDPgrowth_{qt(i,t)} + \beta_p PopOver15_{mt(i,t)} + \sum_{k} \beta_{c,k} \, car_{k,it} \\
& + \sum_{b}^{2} [\delta_b 1\{t \geq \tau_b\} + \gamma_b (t - \tau_b) 1\{t \geq \tau_b\}] \\
& + \sum_{k=1}^{2} \left[\phi_{lag} \sin\left(\frac{2\pi k T}{7 \times 24}\right) + \psi_{lag} \cos\left(\frac{2\pi k T}{7 \times 24}\right) \right] \\
& + \sum_{k=1}^{2} \left[\phi'_{lag} \sin\left(\frac{2\pi k T}{365.25 \times 24}\right) + \psi'_{lag} \cos\left(\frac{2\pi k T}{365.25 \times 24}\right) \right] + C(hour) + C(station) \\
& + \varepsilon_{it}
\end{aligned}
$$

Where $H = 672$ hours ($\pm$ 4 weeks), and the γ_h are the event-hour coefficients.

7 Empirical Results

In this section, I present the results and discuss potential applications of behavioural concepts.

7.1 OLS Regression Analysis

Table 3: OLS Regression: Agg (0), Site (i)

Hourly Log-NO_2 OLS Regression (Clustered SE)

Dependent variable: ***log(NO_2 + 1)***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	1.001***	0.389***	0.665***	0.775***	1.190***	0.641***	1.139***
	(0.103)	(0.082)	(0.088)	(0.130)	(0.156)	(0.089)	(0.127)
C(hour)[T.1]	0.189***	0.021***	0.259***	0.205***	0.137***	0.201***	0.229***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.007)	(0.009)
C(hour)[T.2]	0.079***	-0.040***	0.086***	0.063***	0.089***	0.155***	0.192***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.008)
C(hour)[T.3]	0.009*	-0.079***	0.001	-0.014**	0.063***	0.013**	0.014*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)
C(hour)[T.4]	-0.145***	-0.065***	-0.171***	-0.162***	-0.049***	-0.227***	-0.246***
	(0.006)	(0.005)	(0.006)	(0.008)	(0.009)	(0.006)	(0.008)
C(hour)[T.5]	0.028***	0.199***	-0.059***	-0.030***	-0.041***	-0.064***	-0.014*
	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)	(0.007)	(0.008)
C(hour)[T.6]	0.332***	0.219***	0.305***	0.362***	0.264***	0.339***	0.389***
	(0.006)	(0.005)	(0.005)	(0.008)	(0.009)	(0.006)	(0.007)
C(hour)[T.7]	0.061***	-0.129***	0.108***	0.081***	0.112***	0.119***	0.127***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.006)
C(hour)[T.8]	-0.049***	-0.077***	-0.041***	-0.060***	-0.024***	-0.029***	-0.030***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)
C(hour)[T.9]	-0.011**	0.044***	-0.038***	-0.046***	-0.011	-0.073***	-0.053***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.10]	0.043***	0.052***	0.029***	0.034***	0.096***	-0.006	0.019***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.11]	0.106***	0.056***	0.074***	0.078***	0.090***	0.105***	0.129***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.12]	0.097***	0.036***	0.088***	0.107***	0.064***	0.118***	0.133***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.13]	0.025***	-0.005	0.021***	0.022***	0.038***	0.014***	0.035***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.14]	-0.001	-0.014***	0.001	0.011	0.038***	-0.050***	-0.022***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)
C(hour)[T.15]	0.044***	0.016***	0.036***	0.018***	0.067***	0.024***	0.054***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)
C(hour)[T.16]	0.046***	0.012***	0.039***	0.017***	0.027***	0.075***	0.086***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.17]	0.064***	0.030***	0.032***	0.044***	0.052***	0.082***	0.085***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.18]	0.075***	0.071***	0.039***	0.080***	0.100***	0.025***	0.046***
	(0.006)	(0.005)	(0.005)	(0.008)	(0.008)	(0.005)	(0.007)

C(hour)[T.19]	0.000	-0.005	0.011*	0.022***	0.019**	-0.052***	-0.016**
	(0.006)	(0.005)	(0.006)	(0.008)	(0.009)	(0.006)	(0.008)
C(hour)[T.20]	0.023***	-0.012**	0.013**	0.012*	0.001	0.031***	0.068***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.21]	0.035***	-0.012***	0.033***	0.028***	0.039***	0.047***	0.066***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)
C(hour)[T.22]	0.045***	-0.031***	0.051***	0.017***	0.082***	0.042***	0.040***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
C(hour)[T.23]	0.074***	-0.010	0.066***	0.031***	0.133***	0.087***	0.083***
	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)
C(weekday)[T.1]	0.017***	0.007***	0.018***	0.018***	0.023***	0.021***	0.025***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
C(weekday)[T.2]	0.024***	0.008***	0.026***	0.025***	0.032***	0.028***	0.027***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(weekday)[T.3]	0.026***	0.007***	0.028***	0.027***	0.038***	0.030***	0.027***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
C(weekday)[T.4]	0.027***	0.001	0.029***	0.023***	0.047***	0.036***	0.032***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(month)[T.2]	0.016***	0.016***	0.028***	0.018***	0.018***	0.011**	0.020***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)
C(month)[T.3]	0.138***	0.064***	0.097***	0.104***	0.166***	0.094***	0.158***
	(0.014)	(0.011)	(0.012)	(0.017)	(0.021)	(0.012)	(0.017)
C(month)[T.4]	0.024***	0.012***	0.019***	0.014***	0.029***	0.009***	0.023***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(month)[T.5]	0.014***	-0.000	0.012***	0.020***	0.011***	0.007**	0.020***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(month)[T.6]	0.073***	0.030***	0.055***	0.051***	0.089***	0.053***	0.087***
	(0.008)	(0.006)	(0.007)	(0.010)	(0.011)	(0.007)	(0.010)
C(month)[T.7]	0.007*	0.000	0.010**	0.002	0.010	-0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
C(month)[T.8]	0.023***	0.007**	0.009***	0.024***	0.022***	0.015***	0.023***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
C(month)[T.9]	0.127***	0.044***	0.089***	0.099***	0.156***	0.088***	0.148***
	(0.013)	(0.011)	(0.011)	(0.017)	(0.020)	(0.011)	(0.016)
C(month)[T.10]	0.140***	0.048***	0.096***	0.107***	0.167***	0.090***	0.159***
	(0.015)	(0.012)	(0.013)	(0.020)	(0.023)	(0.013)	(0.019)
C(month)[T.11]	0.153***	0.062***	0.088***	0.121***	0.184***	0.094***	0.174***
	(0.015)	(0.012)	(0.013)	(0.019)	(0.024)	(0.013)	(0.019)
C(month)[T.12]	-0.143***	-0.052***	-0.086***	-0.103***	-0.159***	-0.083***	-0.162***
	(0.017)	(0.013)	(0.014)	(0.021)	(0.025)	(0.014)	(0.020)

Table 3 Continued

C(quarter)[T.2]	0.111***	0.041***	0.086***	0.085***	0.130***	0.068***	0.130***
	(0.011)	(0.009)	(0.010)	(0.014)	(0.016)	(0.010)	(0.014)
C(quarter)[T.3]	0.156***	0.051***	0.108***	0.125***	0.188***	0.099***	0.176***
	(0.016)	(0.013)	(0.014)	(0.021)	(0.025)	(0.014)	(0.021)
C(quarter)[T.4]	0.151***	0.058***	0.098***	0.125***	0.192***	0.101***	0.170***
	(0.014)	(0.012)	(0.012)	(0.018)	(0.022)	(0.012)	(0.018)
C(season)[T.Spring]	0.176***	0.076***	0.127***	0.138***	0.207***	0.109***	0.200***
	(0.017)	(0.014)	(0.015)	(0.021)	(0.026)	(0.015)	(0.021)
C(season)[T.Summer]	0.102***	0.037***	0.074***	0.077***	0.122***	0.065***	0.116***
	(0.011)	(0.009)	(0.010)	(0.014)	(0.017)	(0.010)	(0.014)
C(season)[T.Winter]	0.302***	0.123***	0.190***	0.233***	0.355***	0.195***	0.343***
	(0.032)	(0.025)	(0.027)	(0.040)	(0.048)	(0.027)	(0.039)
D_covid	0.000	-0.023***	-0.073***	-0.076***	0.000***	-0.071***	-0.048***
	(0.000)	(0.006)	(0.006)	(0.021)	(0.000)	(0.006)	(0.009)
lag1_log_NO2	0.849***	0.852***	0.787***	0.824***	0.835***	0.824***	0.805***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
toll_rate	-0.000	0.001***	-0.003***	0.001	0.002***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wind_speed	-0.018***	-0.016***	-0.023***	-0.026***	-0.014***	-0.014***	-0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP_growth	0.003***	0.002***	0.001**	0.001*	0.001***	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pop_over15	-0.000**	0.000**	0.000	0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
bensin_95_oktan	-0.008***	0.006***	0.007***	0.001	-0.009**	0.007***	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
bensin_98_oktan	0.009***	-0.006***	-0.007***	-0.000	0.011***	-0.007***	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
bildäck	-0.001**	-0.000	0.000	-0.000	-0.002***	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
bilförsäkring	0.000	0.001***	0.000***	-0.000**	-0.000*	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
biltillbehör	0.002***	0.000	-0.001***	0.001	0.004***	0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
biltvätt	-0.001	-0.003***	0.002***	-0.002	-0.003**	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
dieselolja	0.000	-0.000*	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
garagekostnad	0.001***	-0.001**	0.000	0.002***	0.002***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 3 Continued

kontrollbesiktning	-0.000***	-0.000***	0.000	-0.001***	-0.002***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
körskoleutbildning	0.001***	-0.000***	0.000	-0.000	-0.001***	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
parkeringsavgifter	-0.003***	0.002***	-0.002***	-0.001	-0.000	0.000	0.005***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
underhållsservice	-0.000***	0.000**	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
daily_sin1	0.121***	0.112***	0.111***	0.104***	0.116***	0.113***	0.104***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
daily_sin2	0.054***	0.088***	0.026***	0.042***	0.027***	0.058***	0.060***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
daily_sin3	-0.085***	-0.032***	-0.092***	-0.092***	-0.063***	-0.126***	-0.121***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
daily_cos1	-0.116***	-0.065***	-0.170***	-0.125***	-0.105***	-0.175***	-0.163***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)
daily_cos2	-0.113***	-0.081***	-0.131***	-0.128***	-0.099***	-0.147***	-0.132***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
daily_cos3	-0.076***	-0.089***	-0.062***	-0.070***	-0.074***	-0.048***	-0.054***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
annual_sin1	-0.002**	0.003**	0.004***	-0.003*	-0.005***	-0.001	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
annual_sin2	-0.002*	0.003***	-0.001	0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
annual_cos1	0.000	0.001	0.002	0.000	-0.001	0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
annual_cos2	-0.002*	-0.001	-0.003**	0.002	-0.000	-0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
R-squared	0.926	0.885	0.849	0.856	0.871	0.857	0.859
R-squared Adj.	0.926	0.885	0.849	0.856	0.871	0.857	0.859
N	65279	96479	130128	77624	64535	127776	87479
Std. Err.	0.163	0.230	0.273	0.278	0.235	0.288	0.282

Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Table 3 Continued
Source: Author's empirical results

The inclusion of the Fourier terms and temporal fixed effects yields extremely high explanatory power, and by absorbing almost all predictable cyclical and site-specific variation, the model isolates the residual variation needed to credibly identify the toll's causal effect. As seen in *Table 3*, there are clearly heterogeneous effects across sites. While some station monitors (3, 6, and 7) exhibit a statistically significant negative toll-rate coefficient, on the order of 0.2 - 0.4% change in hourly NO_2 per SEK, the effect is small, and other stations seem to show even slightly positive (though sometimes marginally significant), however at peak charge levels this could translate into a cumulative 10 – 20% reduction. I could be led to assume that while the charge perhaps reduces NO_2 emissions where traffic volumes are highest but has a negligible impact at lower-volume or more residential monitors. The pollution-mitigation benefits of pricing are likely spatially concentrated in the high-traffic 'downtown' areas.

During the pandemic, the log-NO_2 term is large and highly significant across all sites, signalling strong hourly persistence in pollution levels. While quarterly GDP growth shows a small but often positive association, as expected, population over 15 remains almost at zero – perhaps indicating that today's youth are less interested in leveraging private modes of transport due to increased awareness and sensitivity to the issue of pollution as purchasing power, at least for the average Swedish household, is meaningfully higher now than in 2006. Among car-cost variables, fuel prices occasionally present with the expected negative sign, though in marginal magnitudes, while other components are mixed, implying that operating costs tend to matter less for emissions than the direct per-trip toll, lending some credibility to my hypothesis on the effects of salient pricing.

7.2 Interrupted Time Series Analysis

7.2.1 Baseline Analysis

Table 4: ITS Regression

Interrupted Time-Series Regression (Newey–West HAC(24) SE)

Dependent var: $\log(NO_2 + 1)$

(1)		(2)		(3)	
Intercept	0.370***	I_trial_start	-0.023***	weekly_sin1	0.005***
	(0.011)		(0.005)		(0.001)
lag1_log_no2	0.824***	I_trial_end	-0.003	weekly_cos1	-0.016***
	(0.001)		(0.007)		(0.001)
toll_rate	-0.002***	I_perm_start	0.017***	weekly_sin2	0.006***
	(0.000)		(0.004)		(0.001)
wind_speed	-0.018***	I_price_hike_1	-0.005**	weekly_cos2	-0.005***
	(0.000)		(0.002)		(0.001)
GDP_growth	0.001***	I_price_hike_2	-0.021***	annual_sin1	0.013***
	(0.000)		(0.005)		(0.001)
Pop_over15	0.000***	posttime_trial_start	0.000*	annual_cos1	0.009***
	(0.000)		(0.000)		(0.001)
I_covid	-0.015***	posttime_trial_end	-0.000***	annual_sin2	-0.003***
	(0.004)		(0.000)		(0.001)
		posttime_perm_start	0.000***	annual_cos2	-0.004***
			(0.000)		(0.001)
		posttime_price_hike_1	-0.000***		
			(0.000)		
		posttime_price_hike_2	0.000***		
			(0.000)		
				R-squared	0.859
				Adj. R-squared	0.859
				N	582099
				Std. Err.	0.272

Standard errors (Newey–West) in parentheses. * p<.1, ** p<.05, *** p<.01

Note: The accompanying visualisation can be seen in Appendix C.

Source: Author's empirical results

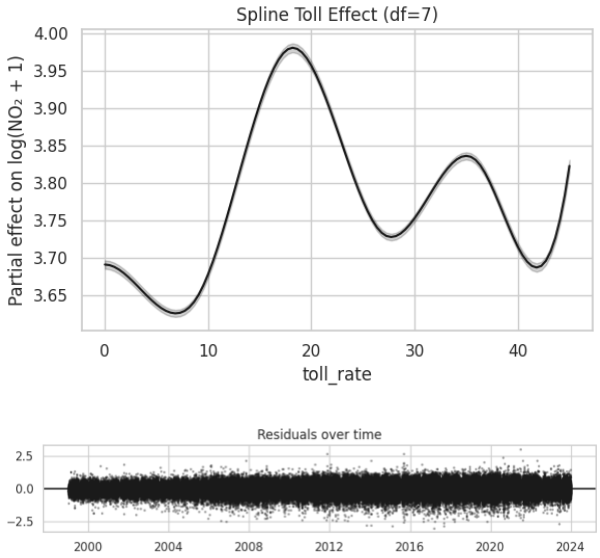
As seen previously in the OLS regression, NO_2 emissions are overwhelmingly driven by levels from the hour prior. Accounting for this persistence of around 82% is essential to isolating policy impacts from pollution inertia. Here, I see that a 1 SEK increase in the congestion fee is associated with around a 2% immediate decline in log-NO_2 emissions, holding all else constant. This replicates and now pools across the site-specific results, underscoring that higher charges consistently work towards reducing emissions. Both macro-controls are statistically significant but remain economically negligible. The COVID dummy captures the 1.5% fall in NO_2 emissions during the lockdown, which is interesting when considering the implications that a pandemic might have had less of a behavioural impact than the levying of a tax.

There is an immediate 2.3% drop ($p < 0.01$) in NO_2 emissions during the trial-period introduction, and the trial-period conclusion yielded another small but statistically insignificant 0.3% in further reduction, likely due to a weak legacy effect. However, it must be noted that the end of the trial did not meaningfully reverse gains, suggesting that behavioural or infrastructural adjustments persisted as people altered their schedules or modes of transport during the taxed period and continued on with the environmentally beneficial behaviour. Surprisingly, there is a 1.7% increase in NO_2 emissions ($p < 0.01$) at the launch of the permanent scheme. While counter-intuitive, it may reflect a ramp-up in public transportation frequency or drivers shifting routes just outside the cordon in ways that may have temporarily worsened local concentrations, which is especially likely as I have already seen that even 1 m/s wind speed disperses NO_2 emissions by 1.8%. This flags an important nuance in congestion pricing theory: not all policy transitions yield monotonic improvements, and, if all aspects are not considered, they can often have a detrimental effect. The Stockholm congestion tax was specifically introduced with its main aim being to reduce traffic volumes, and therefore reduce emissions, though perhaps this mediation in logic was not entirely successful in practice. Both the trial and permanent implementation start to exhibit positive slope adjustments with NO_2 emissions slowly rebounding over time, suggesting habituation or secondary adjustments by drivers.

The first price hike shows a modest 0.5% reduction ($p < 0.05$), consistent with hypothesis 2 that higher fees make more of an impact than simply the presence of a fee. The second price hike shows a substantial 2.1% decrease ($p < 0.01$) in NO_2 emissions, matching the effect of the original trial, suggesting that toll elasticity remains stable over time. Each price hike also induces a negative trend change, implying that the permanent increases in tolls not only lower the immediate level but also sustain a gradual further decline in emissions, lending more support to my theory on there being a threshold to salience. This more impactful effect, as compared to the muted changes in 2006-07, may also be the effect of the rise in the popularity and accessibility of cleaner vehicles.

7.2.2 ITS Spline Analysis

Figure 7: Non-linearity of Congestion Tax Impact



Note: The accompanying visualisations for df = 4 and df = 6 can be seen in Appendix D.

Source: Author's empirical results

As can be seen in *Fig. 7*, there is clearly a non-linear 'dose-response' of toll rate on NO_2 emissions. As evident in the concave-convex pattern, at low charges (0 – 5 SEK), NO_2 responds modestly, dipping slightly – the price is low enough to keep off-peak traffic flowing meaning there is minimal pollution benefit but likely signals broad social acceptability as the tax is not viewed to be unduly unfair to any set target group as the clear statement here is more about retaining awareness in regards to the consequences of pollution rather than creating any measurable decrease in NO_2 emissions or capitalising on it as an opportunity for extra revenue. Ironically, though, while most governments earn most of their congestion tax-based revenue during peak hours, they also likely benefit greatly in terms of revenue from the smallest priced brackets due to sheer volume by capitalising on the fact that, to most people, it would seem to be a minimal cost.

Peak sensitivity however, lies around 15 – 20 SEK as the curve climbs sharply, reaching its maximum partial effect (around 4.0 on the log scale), indicating that each additional krona in this mid-range yields the largest incremental reduction in emissions, this seems to be the goldilocks spot for policy makers to maximise air-quality gains per krona, which could inform dynamic or tiered toll-setting. However, there are diminishing returns beyond 25 SEK as the curve falls, suggesting that further increases in the fee produce smaller marginal benefits, perhaps because the most-price responsive drivers have already adjusted their behaviour, and partially due to the timing – those with fixed routines may be unable to avoid this commute time and it is also likely a time when public transport runs at high frequency, increasing the NO_2 emissions overall. This drives revenue from some of the least-sensitive drivers, though, accepting lower marginal environmental returns. There is then a renewed responsiveness at high fees (45 SEK), which may reflect a response to what drivers perceive as 'prohibitive' fees, as the charges presumably cross a psychologically salient threshold, as is consistent with behavioural models. Interestingly, this is during rush hour, likely meaning that the congestion pricing mechanism has been successful in convincing people to alter their behaviour towards another mode of transport. Beyond a certain

threshold, though, simply raising fees is likely to diminish environmental returns, no matter how the revenue earned is earmarked, and may risk political backlash.

The spline's behaviour beyond 25 SEK argues for a targeted cost-effectiveness analysis as they signal limited environmental gains despite high prices. Although peak-hour surcharges, when most commuters have little choice, raise some equity concerns, they help to blunt the worst of the NO_2 emissions spikes linked to adverse health outcomes. Furthermore, Stockholm's inner city has accessible, frequent, high-quality public transport, meaning that travelling via a private mode of transport is only one choice of many and, therefore, this increased charge is likely not an undue burden on those commuters. This supports the implementation of a two-tier threshold strategy – the kinks at around 10 SEK, where marginal benefit is the lowest, and again at 25 SEK justify a mid-range bracket, with a tier 2 surcharge above that to capture revenue from the most inelastic trips and re-engage residual responsiveness. Instead of a series of smaller hikes, it is likely that drivers will respond better to larger, more clearly signalled jumps between longer time intervals and will, therefore, take more care to avoid certain timeslots.

Table 5: Spline Augmented ITS

ITS Spline Regression (df=7; HAC(24) SE)

Dep var: log(NO_2 + 1)

(1)		(2)		(3)	
Intercept	0.473*** (0.006)	I_trial_start	-0.037*** (0.006)	weekly_sin1	0.011*** (0.001)
lag1_log_no2	0.776*** (0.001)	I_trial_end	0.000 (0.009)	weekly_cos1	-0.022*** (0.001)
toll_s1	0.473*** (0.006)	I_perm_start	0.022*** (0.005)	weekly_sin2	0.011*** (0.001)
toll_s2	-0.000*** (0.000)	I_price_hike_1	0.003 (0.003)	weekly_cos2	-0.002*** (0.001)
toll_s3	-0.225*** (0.001)	I_price_hike_2	-0.074*** (0.006)	annual_sin1	0.018*** (0.001)
toll_s4	0.531*** (0.003)	posttime_trial_start	0.000 (0.000)	annual_cos1	0.011*** (0.001)
toll_s5	-0.160*** (0.002)	posttime_trial_end	-0.000*** (0.000)	annual_sin2	-0.004*** (0.001)
toll_s6	0.351*** (0.003)	posttime_perm_start	0.000*** (0.000)	annual_cos2	-0.005*** (0.001)
toll_s7	-0.156*** (0.004)	posttime_price_hike_1	-0.000*** (0.000)		
toll_s8	0.132*** (0.004)	posttime_price_hike_2	0.000*** (0.000)		
wind_speed	-0.026*** (0.000)				
GDP_growth	0.001*** (0.000)				
Pop_over15	0.000*** (0.000)				
I_covid	-0.013*** (0.004)				
				R-squared	0.829
				Adj. R-squared	0.829
				N	582099
				Std. Err.	0.300

Std. errors (Newey–West) in parentheses; *p<0.1; **p<0.05; ***p<0.01

Note: The accompanying regressions for df = 4 and df = 6 can be seen in Appendix D.

Source: Author's empirical results

Taking a closer look at how different factors fluctuate in *Table 5,* accounting for non-linearity provides some interesting insights. On a hygiene level, the spline basis terms are all highly significant ($p < 0.01$ or 0.05), confirming that the nonlinear specification is justified, with their alternating signs underpinning the shape of the partial-effect curve. The prominent spline coefficients demonstrate that the behavioural response curve is complex and must be considered in-depth when considering policy redesign. While the autoregressive term remains large, wind speed is seen to be slightly larger in magnitude than before (- 0.026), reaffirming its critical role in dispersion. The start of the trial shows a significant – 0.037 level shift, larger than the linear ITS' - 0.023, implying that allowing for nonlinear toll effects reallocates some of the initial trial impact into the spline. The start of the permanent implementation remains positive and confirms the earlier finding of a small rebound at the permanent launch phase. The second price hike is substantially larger in this spline model than the linear ITS (- 0.074 as compared to – 0.021), suggesting that part of the second price-hike effect is captured by the nonlinear toll term, and the remaining direct jump is even more pronounced when flexibly modelling for toll responsiveness. This suggests compositional effects – some of the mid-range toll elasticity was likely previously soaked up by the dummy. The post-time slopes' signs and significance mirror the linear ITS, reinforcing the pattern of slow rebounds versus sustained declines.

The overall fit of this model is slightly lower than the linear ITS' ($R^2 = 0.829$ and 0.859, respectively), reflecting that some policy variation is absorbed by the flexible toll term, rather than through fixed effects or dummies. The residuals are centered and homoscedastic, indicating that the spline-ITS captures both the policy dummies and the nuanced toll effects well with no structural misfits at the typical breakpoints, suggesting that the model cleanly subsumes those fits.

Curiously, however, the first price hike appears, now, to be positive. To investigate this further, I conduct a spatial disaggregation of post-hike residuals to check whether the overall uptick is driven by just a few monitors or if it was an accurate representation. I also plot the raw daily averages of ± 30 days since model residuals and interaction terms are all conditional on my controls and spline terms. A visible rebound here would reflect genuine emissions behaviour. However, as seen in *Fig. 8* and *9*, it is clearly mainly due to Site 1.

Figure 8: Spatial Disaggregation of Residuals

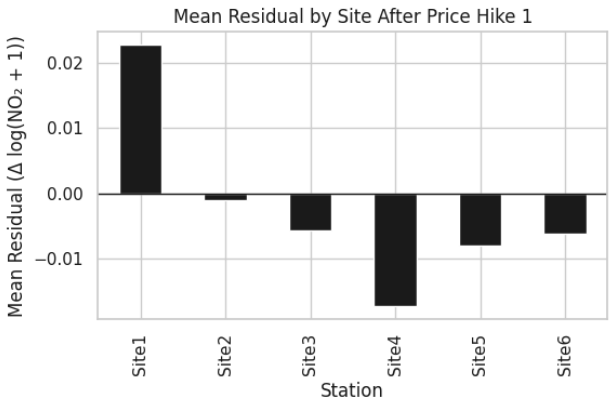
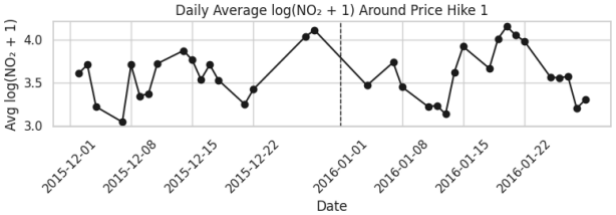


Figure 9: Raw Daily Averages



Note: Similar graphs for the other breakpoints can be found in Figure D.2.

Source: Author's empirical results

I then run a regression during off-peak hours to track any changes in behaviour in the overall dataset by interacting the price-hike dummy with an off-peak indicator to decompose the average post-hike effect into two margins: peak effect and off-peak incremental effect (*Table 6*).

Table 6: Off-peak Interaction

Interaction Model (Price Hike 1)

Dep var: log(NO_2 + 1)

Term	Estimate (Std. Err.)
Intercept	0.863*** (0.041)
lag1_log_no2	0.844*** (0.006)
wind_speed	-0.012*** (0.002)
GDP_growth	0.002*** (0.000)
Pop_over15	-0.000*** (0.000)
I_price_hike_1	-0.045*** (0.011)
offpeak	-0.307*** (0.010)
price1_offpeak	-0.003 (0.008)
R-squared	0.858
Adj. R-squared	0.858
N	582099
Std. Err.	0.274

Source: Author's empirical results

The core treatment effect is now negative and economically meaningful, estimating an immediate 4.5% reduction in NO_2 emissions at peak hours following the first toll increase – very close to the original trial's effect size and consistent with stable long-run toll elasticities. The near-zero coefficient on the off-peak interaction indicates no statistically significant difference in the congestion-price effect between peak and off-peak hours, meaning there is no rebound of emissions in off-peak periods that could explain the earlier anomalous positive coefficient.

7.3 Event Study Analysis

Table 7: Event Study: Breakpoints (1 – 5), Placebo Date (6), Split-sample (7)

Event Study with Spline (±4 Weeks; Cluster SE)

Dependent variable: $\log(NO_2 + 1)$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	1.001***	0.389***	0.665***	0.775***	1.190***	0.641***	1.139***
	(0.103)	(0.082)	(0.088)	(0.130)	(0.156)	(0.089)	(0.127)
C(hour)[T.1]	0.189***	0.021***	0.259***	0.205***	0.137***	0.201***	0.229***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.007)	(0.009)
C(hour)[T.2]	0.079***	-0.040***	0.086***	0.063***	0.089***	0.155***	0.192***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.008)
C(hour)[T.3]	0.009*	-0.079***	0.001	-0.014**	0.063***	0.013**	0.014*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)
C(hour)[T.4]	-0.145***	-0.065***	-0.171***	-0.162***	-0.049***	-0.227***	-0.246***
	(0.006)	(0.005)	(0.006)	(0.008)	(0.009)	(0.006)	(0.008)
C(hour)[T.5]	0.028***	0.199***	-0.059***	-0.030***	-0.041***	-0.064***	-0.014*
	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)	(0.007)	(0.008)
C(hour)[T.6]	0.332***	0.219***	0.305***	0.362***	0.264***	0.339***	0.389***
	(0.006)	(0.005)	(0.005)	(0.008)	(0.009)	(0.006)	(0.007)
C(hour)[T.7]	0.061***	-0.129***	0.108***	0.081***	0.112***	0.119***	0.127***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.006)
C(hour)[T.8]	-0.049***	-0.077***	-0.041***	-0.060***	-0.024***	-0.029***	-0.030***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)
C(hour)[T.9]	-0.011**	0.044***	-0.038***	-0.046***	-0.011	-0.073***	-0.053***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.10]	0.043***	0.052***	0.029***	0.034***	0.096***	-0.006	0.019***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.11]	0.106***	0.056***	0.074***	0.078***	0.090***	0.105***	0.129***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.12]	0.097***	0.036***	0.088***	0.107***	0.064***	0.118***	0.133***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.13]	0.025***	-0.005	0.021***	0.022***	0.038***	0.014***	0.035***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.14]	-0.001	-0.014***	0.001	0.011	0.038***	-0.050***	-0.022***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)
C(hour)[T.15]	0.044***	0.016***	0.036***	0.018***	0.067***	0.024***	0.054***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)
C(hour)[T.16]	0.046***	0.012***	0.039***	0.017***	0.027***	0.075***	0.086***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.17]	0.064***	0.030***	0.032***	0.044***	0.052***	0.082***	0.085***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
C(hour)[T.18]	0.075***	0.071***	0.039***	0.080***	0.100***	0.025***	0.046***
	(0.006)	(0.005)	(0.005)	(0.008)	(0.008)	(0.005)	(0.007)

C(hour)[T.19]	0.000	-0.005	0.011*	0.022***	0.019**	-0.052***	-0.016**
	(0.006)	(0.005)	(0.006)	(0.008)	(0.009)	(0.006)	(0.008)
C(hour)[T.20]	0.023***	-0.012**	0.013**	0.012*	0.001	0.031***	0.068***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
C(hour)[T.21]	0.035***	-0.012***	0.033***	0.028***	0.039***	0.047***	0.066***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)
C(hour)[T.22]	0.045***	-0.031***	0.051***	0.017***	0.082***	0.042***	0.040***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
C(hour)[T.23]	0.074***	-0.010	0.066***	0.031***	0.133***	0.087***	0.083***
	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)
C(weekday)[T.1]	0.017***	0.007***	0.018***	0.018***	0.023***	0.021***	0.025***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
C(weekday)[T.2]	0.024***	0.008***	0.026***	0.025***	0.032***	0.028***	0.027***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(weekday)[T.3]	0.026***	0.007***	0.028***	0.027***	0.038***	0.030***	0.027***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
C(weekday)[T.4]	0.027***	0.001	0.029***	0.023***	0.047***	0.036***	0.032***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(month)[T.2]	0.016***	0.016***	0.028***	0.018***	0.018***	0.011**	0.020***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)
C(month)[T.3]	0.138***	0.064***	0.097***	0.104***	0.166***	0.094***	0.158***
	(0.014)	(0.011)	(0.012)	(0.017)	(0.021)	(0.012)	(0.017)
C(month)[T.4]	0.024***	0.012***	0.019***	0.014***	0.029***	0.009***	0.023***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(month)[T.5]	0.014***	-0.000	0.012***	0.020***	0.011***	0.007**	0.020***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
C(month)[T.6]	0.073***	0.030***	0.055***	0.051***	0.089***	0.053***	0.087***
	(0.008)	(0.006)	(0.007)	(0.010)	(0.011)	(0.007)	(0.010)
C(month)[T.7]	0.007*	0.000	0.010**	0.002	0.010	-0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
C(month)[T.8]	0.023***	0.007**	0.009***	0.024***	0.022***	0.015***	0.023***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
C(month)[T.9]	0.127***	0.044***	0.089***	0.099***	0.156***	0.088***	0.148***
	(0.013)	(0.011)	(0.011)	(0.017)	(0.020)	(0.011)	(0.016)
C(month)[T.10]	0.140***	0.048***	0.096***	0.107***	0.167***	0.090***	0.159***
	(0.015)	(0.012)	(0.013)	(0.020)	(0.023)	(0.013)	(0.019)
C(month)[T.11]	0.153***	0.062***	0.088***	0.121***	0.184***	0.094***	0.174***
	(0.015)	(0.012)	(0.013)	(0.019)	(0.024)	(0.013)	(0.019)
C(month)[T.12]	-0.143***	-0.052***	-0.086***	-0.103***	-0.159***	-0.083***	-0.162***
	(0.017)	(0.013)	(0.014)	(0.021)	(0.025)	(0.014)	(0.020)

Table 7 Continued

C(quarter)[T.2]	0.111***	0.041***	0.086***	0.085***	0.130***	0.068***	0.130***
	(0.011)	(0.009)	(0.010)	(0.014)	(0.016)	(0.010)	(0.014)
C(quarter)[T.3]	0.156***	0.051***	0.108***	0.125***	0.188***	0.099***	0.176***
	(0.016)	(0.013)	(0.014)	(0.021)	(0.025)	(0.014)	(0.021)
C(quarter)[T.4]	0.151***	0.058***	0.098***	0.125***	0.192***	0.101***	0.170***
	(0.014)	(0.012)	(0.012)	(0.018)	(0.022)	(0.012)	(0.018)
C(season)[T.Spring]	0.176***	0.076***	0.127***	0.138***	0.207***	0.109***	0.200***
	(0.017)	(0.014)	(0.015)	(0.021)	(0.026)	(0.015)	(0.021)
C(season)[T.Summer]	0.102***	0.037***	0.074***	0.077***	0.122***	0.065***	0.116***
	(0.011)	(0.009)	(0.010)	(0.014)	(0.017)	(0.010)	(0.014)
C(season)[T.Winter]	0.302***	0.123***	0.190***	0.233***	0.355***	0.195***	0.343***
	(0.032)	(0.025)	(0.027)	(0.040)	(0.048)	(0.027)	(0.039)
D_covid	0.000	-0.023***	-0.073***	-0.076***	0.000***	-0.071***	-0.048***
	(0.000)	(0.006)	(0.006)	(0.021)	(0.000)	(0.006)	(0.009)
lag1_log_NO2	0.849***	0.852***	0.787***	0.824***	0.835***	0.824***	0.805***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
toll_rate	-0.000	0.001***	-0.003***	0.001	0.002***	-0.004***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wind_speed	-0.018***	-0.016***	-0.023***	-0.026***	-0.014***	-0.014***	-0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP_growth	0.003***	0.002***	0.001**	0.001*	0.001***	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pop_over15	-0.000**	0.000**	0.000	0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
bensin_95_oktan	-0.008***	0.006***	0.007***	0.001	-0.009**	0.007***	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
bensin_98_oktan	0.009***	-0.006***	-0.007***	-0.000	0.011***	-0.007***	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
bildäck	-0.001**	-0.000	0.000	-0.000	-0.002***	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
bilförsäkring	0.000	0.001***	0.000***	-0.000**	-0.000*	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
biltillbehör	0.002***	0.000	-0.001***	0.001	0.004***	0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
biltvätt	-0.001	-0.003***	0.002***	-0.002	-0.003**	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
dieselolja	0.000	-0.000*	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
garagekostnad	0.001***	-0.001**	0.000	0.002***	0.002***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 7 Continued

kontrollbesiktning	-0.000***	-0.000***	0.000	-0.001***	-0.002***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
körskoleutbildning	0.001***	-0.000***	0.000	-0.000	-0.001***	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
parkeringsavgifter	-0.003***	0.002***	-0.002***	-0.001	-0.000	0.000	0.005***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
underhållsservice	-0.000***	0.000**	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
daily_sin1	0.121***	0.112***	0.111***	0.104***	0.116***	0.113***	0.104***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
daily_sin2	0.054***	0.088***	0.026***	0.042***	0.027***	0.058***	0.060***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
daily_sin3	-0.085***	-0.032***	-0.092***	-0.092***	-0.063***	-0.126***	-0.121***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
daily_cos1	-0.116***	-0.065***	-0.170***	-0.125***	-0.105***	-0.175***	-0.163***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)
daily_cos2	-0.113***	-0.081***	-0.131***	-0.128***	-0.099***	-0.147***	-0.132***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
daily_cos3	-0.076***	-0.089***	-0.062***	-0.070***	-0.074***	-0.048***	-0.054***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
annual_sin1	-0.002**	0.003**	0.004***	-0.003*	-0.005***	-0.001	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
annual_sin2	-0.002*	0.003***	-0.001	0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
annual_cos1	0.000	0.001	0.002	0.000	-0.001	0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
annual_cos2	-0.002*	-0.001	-0.003**	0.002	-0.000	-0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
R-squared	0.926	0.885	0.849	0.856	0.871	0.857	0.859
R-squared Adj.	0.926	0.885	0.849	0.856	0.871	0.857	0.859
N	65279	96479	130128	77624	64535	127776	87479
Std. Err.	0.163	0.230	0.273	0.278	0.235	0.288	0.282

Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

Table 7 Continued
Source: Author's empirical results

7.3.1 Policy-by-policy Dynamics

Pre-trends appear consistent as the coefficients on the weekday dummies exhibit no systematic upward or downward trend immediately before each intervention date in *Table 7*. In particular, there is no significant monotonic drift in the 0-4 weeks leading up to each break, bolstering the parallel trend assumption. Since I include the prevailing toll as a covariate, small fluctuations in hour-to-hour charges prior to the shock don't confound the relative-hour estimates either. The placebo date (*col. 6*) shows clusters around zero, and the split-sample (*col. 7*) evidently recovers the same qualitative pattern, confirming that the estimated impacts for real shocks don't vanish or reverse once earlier data is dropped, building confidence that the effects aren't driven by some idiosyncratic anomaly in one subperiod.

The immediate 'post' dummies (+1 to +4 weeks) trace the timing of the treatment effect. Trial start (*col. 1*) shows a modest, delayed decline in NO_2 emissions beginning roughly 1-2 weeks after January 3rd 2006, consistent with an adjustment period as commuters find new routes or modes of transportation. Trial end (*col. 2*), on the other hand, exhibits a small rebound with positive coefficients post-July 31st 2006, indicating that emissions drifted back upward when the toll concession expired as the legacy effect diminished. Permanent start (*col. 3*) is met with a downward jump emerging within days of August 1st 2007, and then sustaining for several weeks. Price hike 1 (*col. 4*) delivers a sharper, more pronounced dip immediately post-January 1st 2016, peaking around the second week and then gradually converging. Price hike 2 (*col. 5*) shows a smaller, shorter-lived decline after January 1st 2020, potentially attenuated by pandemic-era traffic patterns coinciding with the hike.

When I compare the columns, it is evident that larger policy jumps (permanent start, price hike 1) generate both larger magnitude and longer-lasting negative reductions in emissions. While price hike 1 caused a roughly 3 – 4% immediate reduction peaking in week 2, price hike only delivered around 1.5%, which faded by week 3. Joint evidence therefore strengthens the idea that elasticities are both non-linear and context-dependent, and that it is threshold-oriented pricing that tends to drive sustained improvements, whereas small, uniform tweaks may only produce fleeting gains as emissions tend to start to increase once the salience of the toll change dissipates.

8 Discussion

This section synthesises the empirical evidence I have found on hourly NO_2 emissions and situates it within a wider policy conversation on congestion charging. Three key themes emerge from the ITS, OLS, spline, and event-study results: effectiveness, behavioural response, and design trade-offs.

8.1 Effectiveness across Policy Milestones

my interrupted time-series estimates reveal that the 2006 trial led to an immediate 2.3% reduction in log-NO_2 concentrations ($p < 0.01$), with a further, albeit smaller, 0.3% decline at the trial's conclusion. This sustained drop underscores the potential found even in temporary cordon charges. In contrast, the conversion to a permanent scheme in 2007 was unexpectedly met by a 1.7% increase in NO_2 emissions ($p < 0.01$), suggesting short-term route re-optimisation or modal shifts that temporarily worsened local conditions. However, the subsequent 2016 tariff increase generated a renewed 0.5% fall ($p < 0.05$), and the 2020 hike delivered a 2.1% reduction ($p < 0.01$), mirroring the original trial's environmental dividend. These findings only partially supported H1 – while the trial's and the hikes' magnitudes were comparable, the permanent implementation phase exhibited anomalous rebound dynamics. The spline-augmented ITS uncovers a non-linear 'dose-response' whereby marginal abatement per krona peaks in the mid-range (around 15 – 20 SEK), before tapering off at lower (< 5 SEK) and comparatively higher (>25 SEK) fees. This concave-convex pattern suggests that moderate surcharges deliver the greatest pollution reductions per krona, while further increases yield diminishing returns until the next threshold is met.

8.2 The Behavioural Economic Lens

Behavioural theory helps explain these non-monotonic responses. Prospect theory posits that drivers perceive the initial 2006 charge as a salient 'loss' to the free-road status quo, triggering avoidance behaviours that translated into significant NO_2 emissions abatements. Over time, however, loss aversion attenuates as the fee becomes normalised, muting further gains at the 2007 permanent launch (contrary to naive rational-actor predictions). The sharper declines following the 2016 and 2020 hikes suggest that crossing new salient thresholds re-engaged behavioural adjustments, consistent with Chetty et al.'s salience framework. Fairness heuristics likely also played a role as the 2006 referendum conferred democratic legitimacy, reducing perceptions of arbitrariness and cementing public buy-in. Conversely, the absence of dynamic pricing or income-based rebates may have constrained further behavioural shifts during off-peak hours, as drivers weigh concerns against marginal cost savings. my peak-period dominance hypothesis (H3) finds qualified support: while event-study dynamics show more pronounced instantaneous drops during peak-priced hours, off-peak rebounds remain statistically muted, indicating that scheduling flexibility alone does not fully explain the mid-range tariff effects.

While the current structure applies most behavioural concepts well, it could do better by capitalising more on present bias and hyperbolic discounting, by sending out invoices every fortnight rather than every month, though this would have to be weighted against the impact that the magnitude of payment has. There is also little focus on distributive fairness, whether it be vertical of horizontal equity as flat tolls are regressive in percentage terms, and it does not seem conducive for identical users to pay the same fee despite different emissions impacts.

8.3 Limitations and Potential for Extensions for NO2 Emissions

8.3.1 Omitted Variables and Potential Confounders

Although the empirical strategy controls for macroeconomic activity, demographic pressure, seasonality, and site-specific fixed effects, it lacks direct measures of several determinants of urban traffic NO_2 emissions, which could not be included in this thesis due to a lack of access to suitably granular data. In particular, including a broader range of meteorological conditions would likely have provided interesting and significant insights, as the coarse treatment of seasonality and weather cannot account for episodic meteorological events. For the ITS, the absence of a formal control group means that its design relies on the counterfactual assumption that in the absence of congestion pricing, pre-existing trends would have remained unchanged, complicating causal attribution. NO_2 emissions are likely to have been impacted by parallel regulatory initiatives such as the establishment of low-emission zones and tightening standards, which could all covary with the toll schedule.

8.3.2 Spatial Heterogeneity and Spillover Effects

Some critics argue that congestion pricing merely redistributes pollution as traffic may be displaced to un-tolled corridors or to outer suburbs not covered by the monitors. While pooling the six stations with fixed effects assumes that pricing would impact each station uniformly, blunting this concern for the cordon, future work should include geographical data as well. However, stations adjacent to major roads are likely to respond quite differently to more isolated stations, and while I tried to address this by accounting for centrally located stations, unexpected traffic

diversions would impact each station differently on the basis of the average traffic flow in the area. This could be addressed via a spatial econometric framework in which one could incorporate spatial-lag or geographically weighted regressions, especially when considering how much of an impact wind speed could have on NO_2 emissions.

8.3.3 Investigating Equity

In future research, I believe it would be interesting to link household travel surveys to emissions data, to more concretely quantify who pays and who benefits, informing equitable tariff design. Replicating the threshold analysis in other cities would also be interesting in determining whether the salience point is context-invariant as a proportion of average income, or whether different attitudes towards sustainability initiatives or public goods influence it differently.

9 Conclusion

This thesis set out to: (i) investigate whether the perceived permanence of the tax had an impact on NO_2 emissions; (ii) disentangle price presence from price magnitude; (iii) trace temporal and spatial heterogeneity in the response.

H1 has been disproven – the seven-month trial induced a significant, immediate drop in log-NO_2, whereas, in contrast, the transition to the permanent scheme was unexpectedly met with an increase followed by a slow rebound thereafter. Rather than producing equivalent abatement, this suggests that once drivers adjust during the trial, once absent of a sufficiently salient charge, it is easy for them to lose momentum in sticking with these behavioural changes and easier for them to justify paying a fee later on. This, however, would be interesting to investigate in cities with longer/shorter trial periods to see where the threshold lies in habit formation.

Both the tariff magnitude effect (H2), and the peak vs. off-peak dominance (H3) are supported by this thesis. The first post-baseline hike on January 1st 2016 generated a 0.5% reduction in NO_2 emissions ($p < 0.05$), whereas the flat fee from 2007 – 2015 yielded no significant change in emissions. Raising the tariff beyond the baseline level produced a measurable additional abatement. However, the modest magnitude indicates diminishing returns for small-to-moderate hikes and underscores the need to identify fee bands that maximise cost effectiveness. Disaggregating the 2016 effect by time of day reveals an immediate 4.5% reduction in NO_2 emissions during peak-priced hours, and a near-zero incremental change off-peak, indicating no rebound in uncharged periods. Clearly, behavioural responses are concentrated when the price gradient is highest, affirming that commuters likely shift travel schedules or mode most sharply under peak surcharges.

While Börjesson et al. (2012) reported a 28% reduction in traffic volumes during the trial, implying a large behavioural response, the data suggests that such traffic reductions translate into more modest emissions gains, likely because the remaining vehicles emit disproportionately (either due to cold starts or diesel share) and are affected by additional dispersion dynamics. The tariff-hike magnitudes are also smaller in percentage terms than London's ULEZ or Singapore's ERP, reflecting a narrower policy scope as expected due to this being a pure congestion fee as opposed to the implementation of a combined emissions zone, but they echo the same observations regarding larger gains to be found at salient fee levels.

Overall, Stockholm's typical hourly NO_2 emissions levels of around 20–30 $\mu g/m^3$ sit at around two to three times above the World Health Organisation's (WHO) recommended guideline

for around 10 μg/m³, and just below the EU standard of around 40 μg/m³, suggesting that stricter policy standards would be beneficial.

9.1 Perspective on Pigouvian Pricing

Congestion charges are often presented as textbook Pigouvian taxes, but in practice, three main critiques surface:

(i) Regressivity: flat fees disproportionately burden lower-income commuters.
(ii) Political acceptability: voters resist perceived 'new taxes', especially when the benefits are diffused.
(iii) Second-best complications: in the presence of imperfect competition in transit markets or unpriced suburban roads, a single cordon charge may merely displace traffic and pollution.

my findings nuance the topic by highlighting behaviourally conditioned externality correction. Charges below behavioural salience thresholds prove largely symbolic, challenging the assumption that any positive price yields welfare gains. Instead, welfare improvements accumulate as drivers adjust habits in response to sufficiently salient fees – a dynamic dimension often absent from static Pigouvian models.

9.2 Policy Design Implications

The kinks in the spline analysis suggest that progressive tariff bands may be superior to small, uniform hikes. Threshold-oriented pricing in a two-tier system, a moderate baseline with a high peak charge, could maximise abatement per krona while preserving political acceptability for off-peak drivers and generating more consistent revenue for the government to reinvest in improving public transport alternatives. Though in finding an optimal fee band from a revenue earnings perspective, it seems that mid-range increases would be the most cost-effective.

Alternatively, while Stockholm still relies on a fixed schedule, the strong hourly persistence hints that real-time, demand-responsive, dynamic pricing (as in Singapore's ERP) could capture additional gains by targeting days with adverse meteorology or atypical demand spikes, though the lack of complete transparency may be unhelpful to encourage behavioural shifts. Time-differentiated pricing allows for concentrating charges on the hours most likely to cause significant health risks while maintaining modest rates at other times to preserve equity and network accessibility.

I must also consider how the policy impacts revenue recycling and equity because the external benefits accrue city-wide, but fees fall on weekday motorists, especially for those who commute to jobs at regular working hours. Earmarking revenues for public transport or active-mobility infrastructure would widen distributional support and amplify environmental returns. While the six stations investigated in this study are all in areas with high-quality and high-frequency public transport, meaning that utilising private transportation is an active choice in the presence of another accessible alternative and is unlikely therefore to put undue pressure on these weekday motorists, the mechanism would have to be adjusted if expanding to more suburban areas. Differential tolls to preserve social equity could also be considered, by income or by neighbourhood, to preserve efficiency while attenuating equity objections.

In terms of the overall objective, policymakers should also be encouraged to view pricing and technology as mutually reinforcing rather than substitutes. The muted 2007 effect compared to the steady downward decline indicates that the congestion charging's environmental dividend

grows as the fleet gets cleaner. If congestion is not as much of a concern as environmental outcomes, perhaps policymakers should consider excluding electric vehicles from the toll again, or, alternatively, establish lower charges for vehicles running on electricity or greener fuels to encourage the shift. By rigorously testing H1 – H3, this thesis demonstrates that congestion pricing's environmental success hinges not merely on the presence of a fee, but on its strategic calibration to human perceptions and travel behaviour. Policymakers should engage in dynamic re-evaluation of behavioural thresholds over time and adjust schedules to maintain policy potency to avoid an initially salient fee fading into background noise. Future work should explore how these behavioural thresholds vary across contexts and over time, enabling even more nuanced, equitable urban-emission policies.

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Appendix

Appendix A: Summary Statistics

Table A.1: Summary Statistics for NO_2 Datasets

Dataset	Count	Mean	Std.	Min.	25%	50%	75%	Max.
df0_final_imputed	105168.0	221.853423	117.185071	12.7000	128.8	204.7	299.9	1112.4
df1_final_imputed	154608.0	32.301106	20.424879	0.1000	16.8	28.2	43.9	200.0
df2_final_imputed	217560.0	41.995942	26.322780	0.4700	21.1	37.1	58.5	238.9
df3_final_imputed	124521.0	35.888654	24.035874	0.1000	16.9	30.8	50.0	514.1
df4_final_imputed	103848.0	39.231130	22.848883	0.6000	21.6	35.3	53.3	301.4
df5_final_imputed	213816.0	34.334334	23.911147	0.0721	15.8	28.8	47.7	267.6
df6_final_imputed	140304.0	29.828597	22.085873	0.0420	13.1	24.0	40.8	290.6

Appendix B: Research Design Visualisations

Figure B.1: Comparing ± 3 and ± 3.5 Standard Deviations

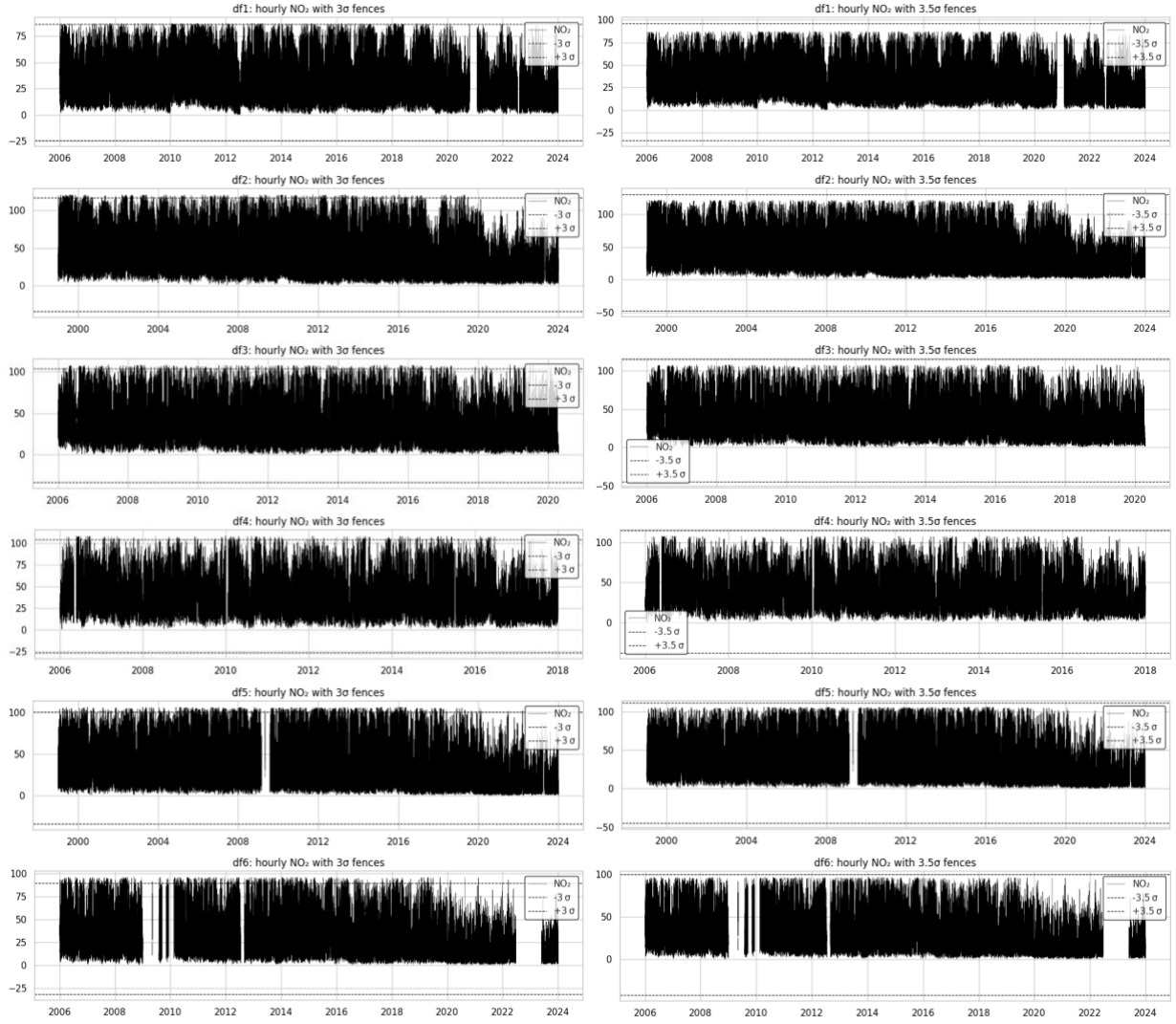


Table B.1: Missing Values per Dataset

Dataset	Total Rows	Missing Count	Missing (%)
Lilla_Essingen_NO2	157752	4323	2.74%
Hornsgatan_108_Gata_NO2	219120	4334	1.98%
Hornsgatan_85_Gatuniva_NO2	125265	2343	1.87%
Norrlandsgatan_29_NO2	105168	2749	2.61%
Sveavagen_59_Gata_NO2	219120	7877	3.59%
Sveavagen_88_Gata_NO2	157752	19113	12.12%
All_Communes_NO2	105168	15483	14.72%

Table B.2: Missing Values per Dataset

Hour	All	df1	df2	df3	df4	df5	df6
0	625	157	85	174	110	321	799
1	661	190	104	179	111	480	845
2	676	205	113	198	123	370	836
3	674	213	121	185	118	338	813
4	687	189	112	189	126	354	821
5	670	192	97	194	131	343	811
6	680	189	103	198	133	328	804
7	691	198	109	196	135	330	801
8	687	200	103	199	134	332	802
9	685	203	107	197	132	323	792
10	682	208	109	189	121	346	804
11	642	186	97	183	113	315	785
12	645	177	93	192	116	316	791
13	669	205	116	182	106	355	814
14	663	200	113	188	105	330	803
15	624	173	99	175	103	316	786
16	603	164	89	164	98	303	783
17	595	160	86	163	100	296	773
18	592	149	78	162	102	292	773
19	600	152	79	162	104	295	774
20	600	150	82	161	104	297	770
21	602	154	80	163	107	292	773
22	609	158	84	163	107	299	779
23	621	162	84	167	110	306	781

Figure B.2: Missingness by Hour (1), and by Day (2)

(1) **(2)**

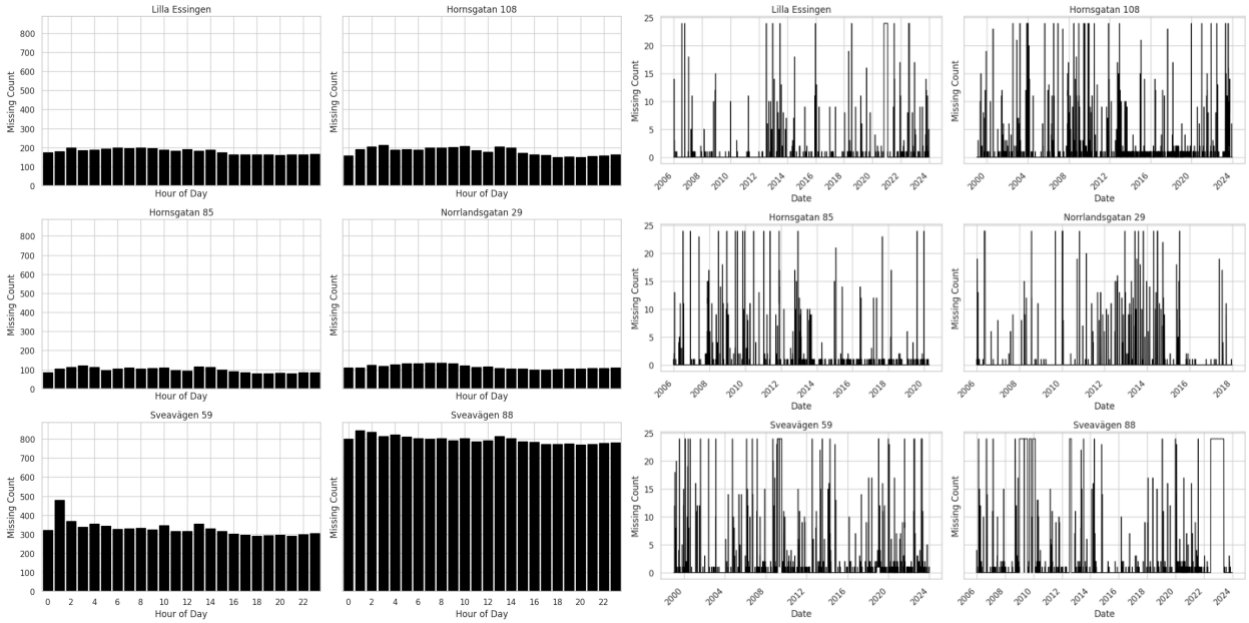


Table B.3: Missingness by Hour (1), and by Day (2)

	Site	Comparison	Mean Δ (µg/m³)	Std Dev (µg/m³)
0	Site1	2w vs 4w	0.004	0.193
1	Site1	3w vs 4w	0.002	0.111
2	Site2	2w vs 4w	- 0.001	0.299
3	Site2	3w vs 4w	- 0.001	0.163
4	Site3	2w vs 4w	0.000	0.300
5	Site3	3w vs 4w	- 0.001	0.148
6	Site4	2w vs 4w	- 0.001	0.412
7	Site4	3w vs 4w	- 0.001	0.174
8	Site5	2w vs 4w	0.000	0.246
9	Site5	3w vs 4w	0.001	0.142
10	Site6	2w vs 4w	- 0.001	0.305
11	Site6	3w vs 4w	0.000	0.159

Figure B.3: Sensitivity Plots: 2w vs 4w (1), and 3w vs 4w (2)

(1) **(2)**

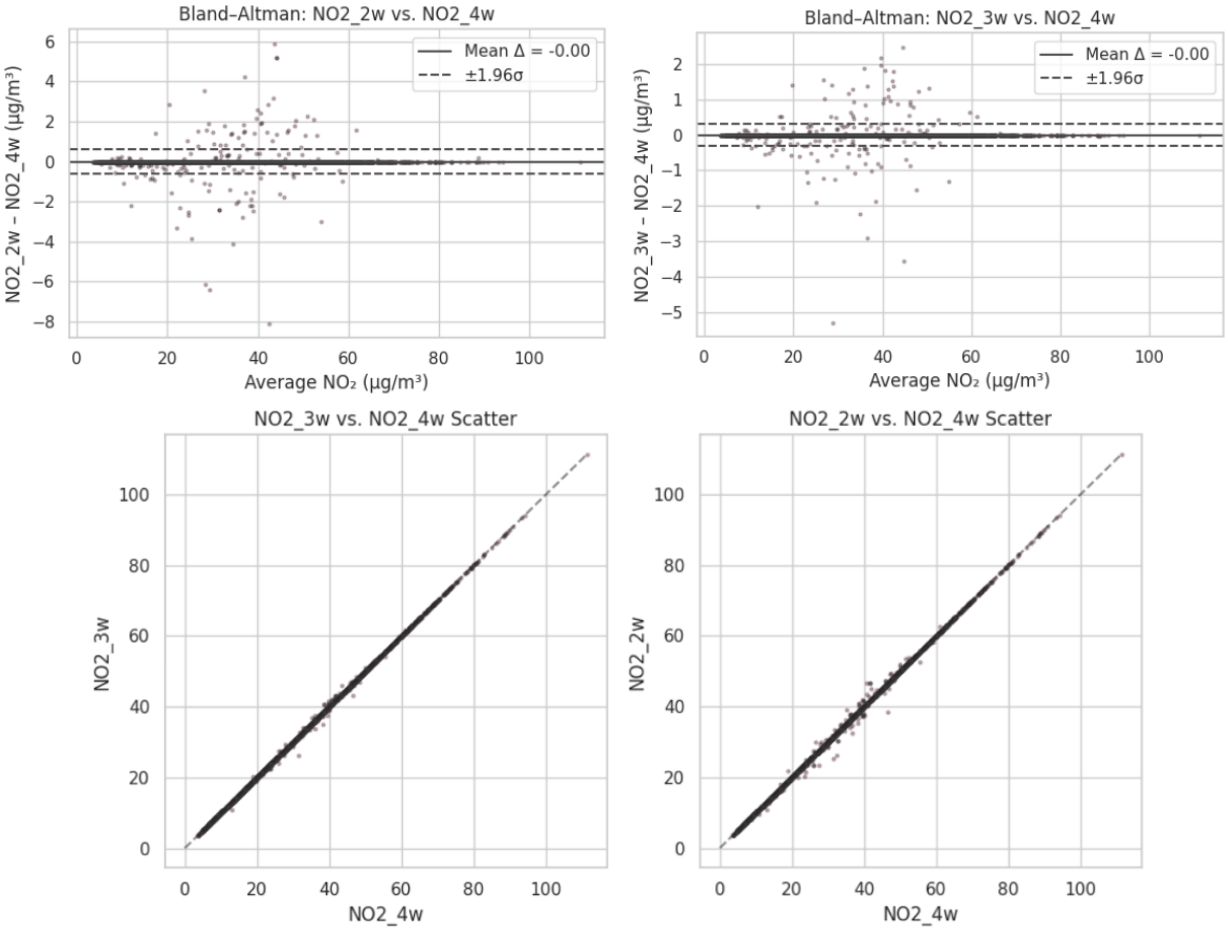
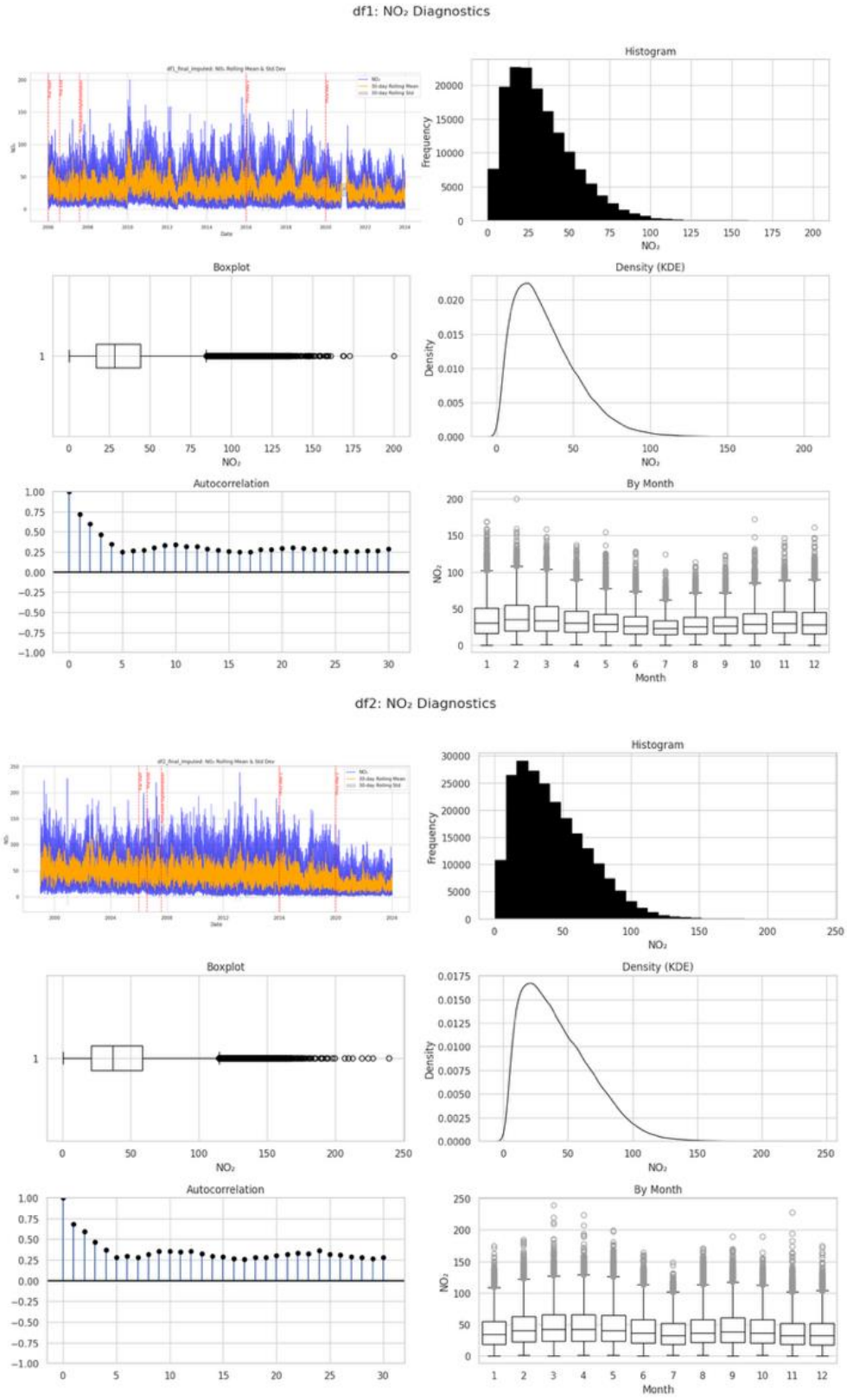


Figure B.4: Summary Plots



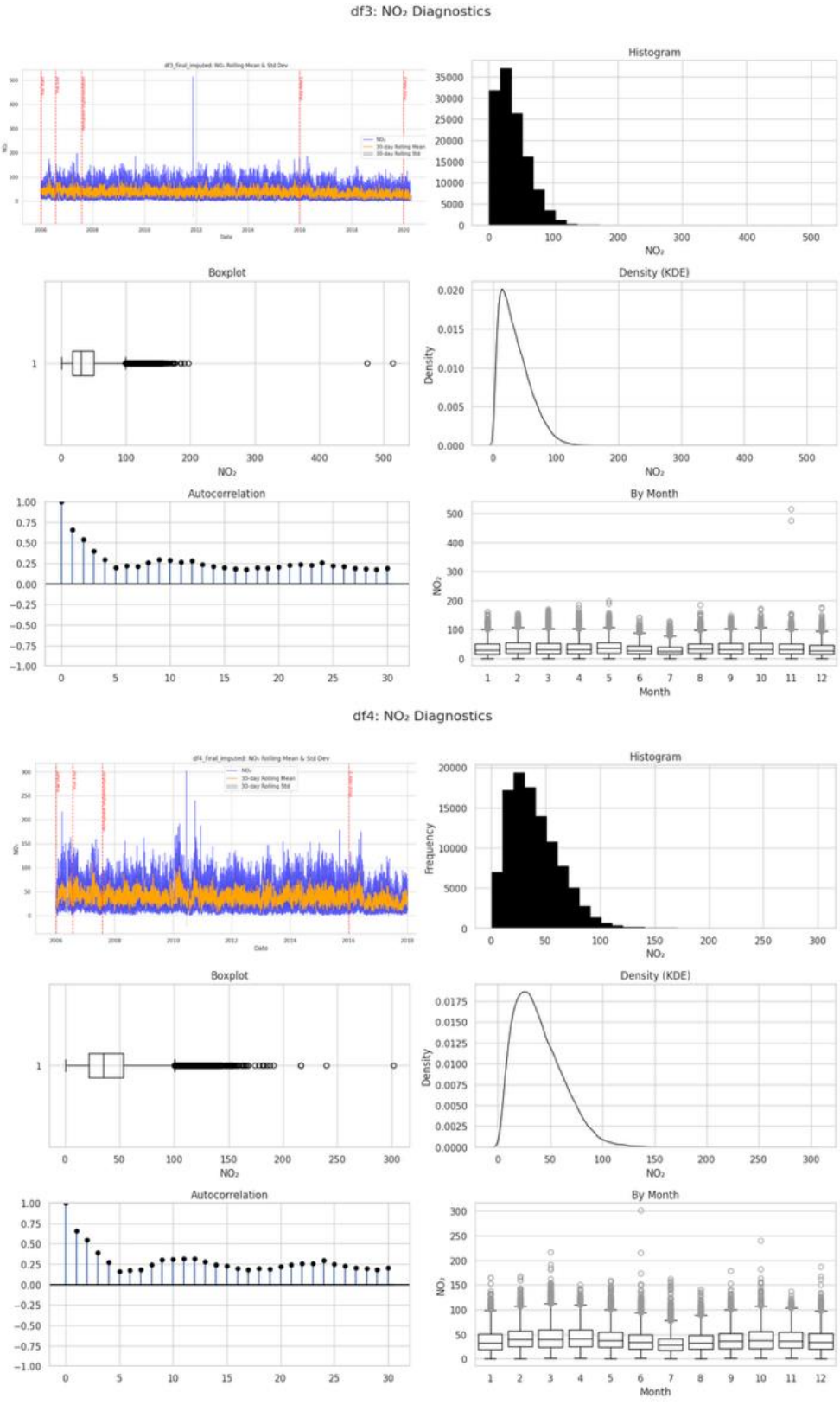


Fig. B.4 Continued

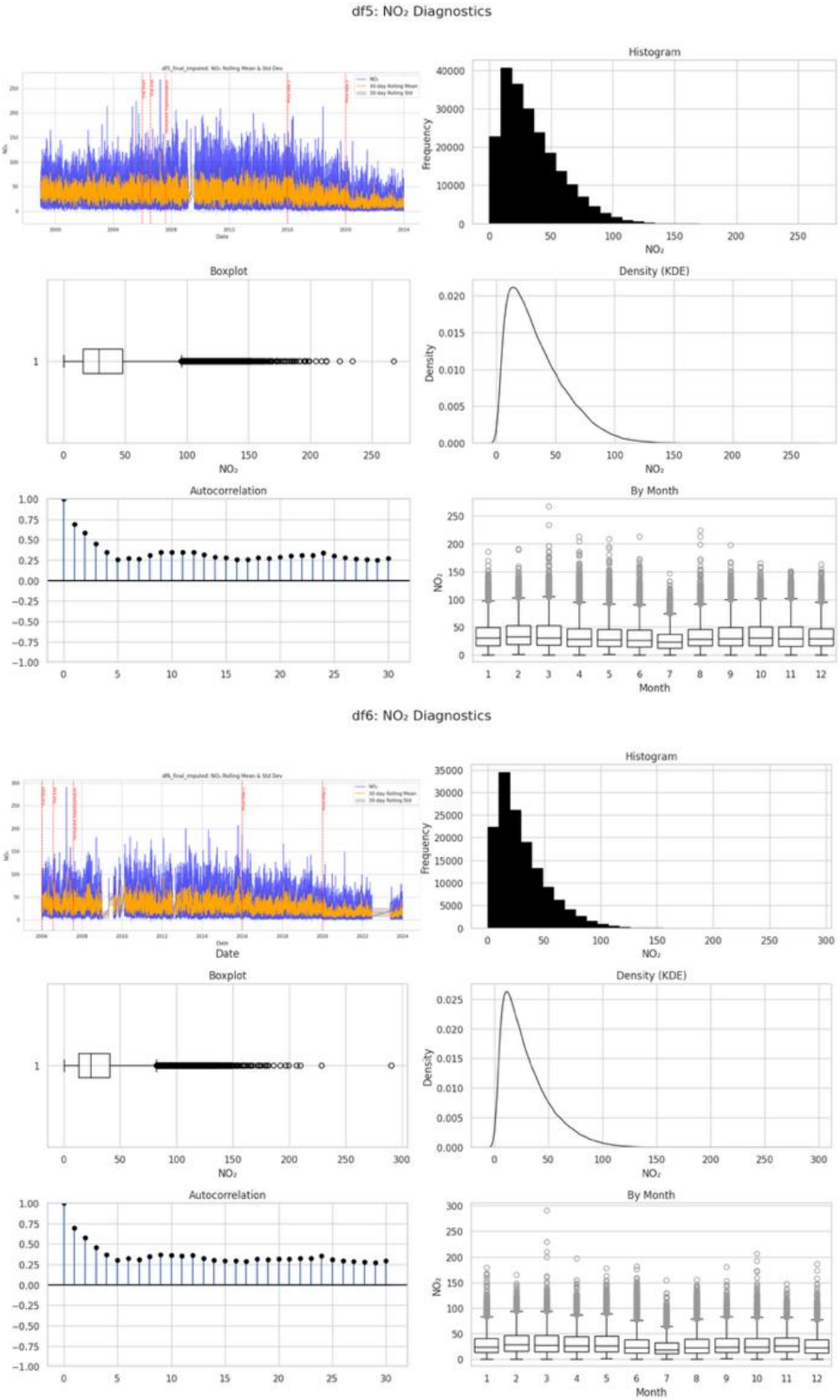
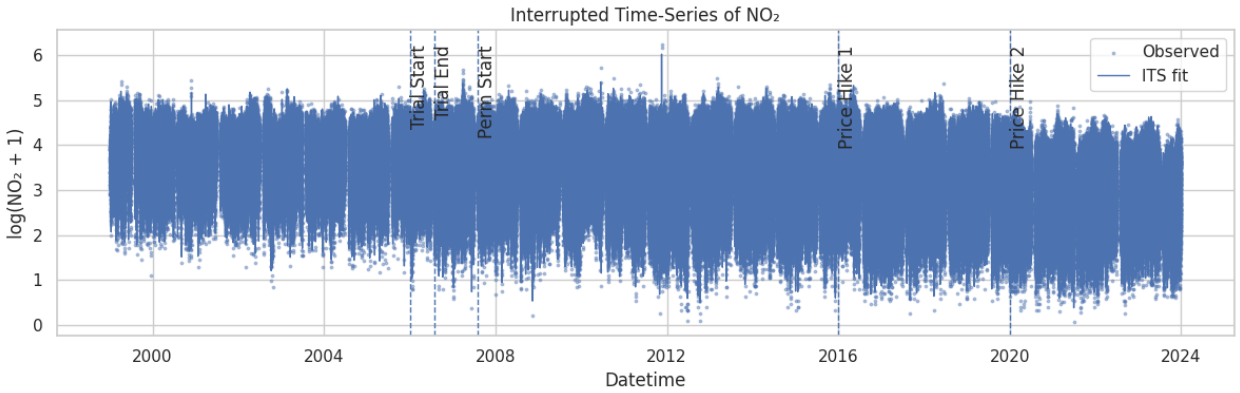


Fig. B.4 Continued

Appendix C: Interrupted Time-Series

Figure C.1: ITS Plot



Appendix D: Spline Augmented ITS

Figure D.1: Spline Plots: df = 4 (1), df = 6 (2)

(1) **(2)**

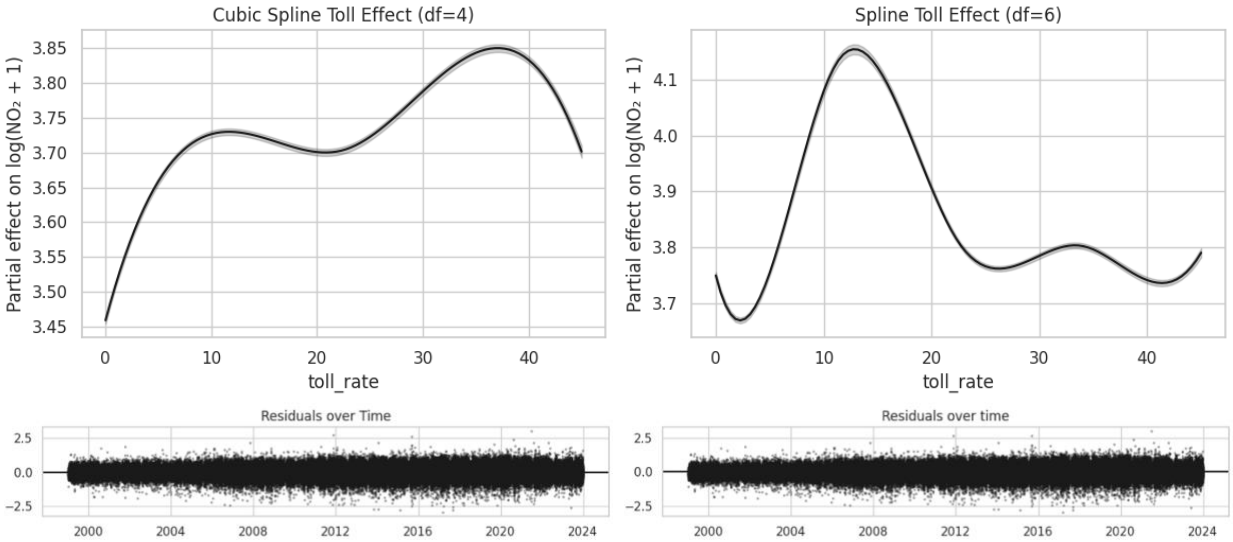


Table D.1: ITS Spline: df = 4 (1), df = 6 (2)

(1)

ITS Spline Regression (df=4; HAC(24) SE)

Dependent var: log(NO₂ + 1)

(1)		(2)		(3)	
Intercept	0.378*** (0.007)	I_trial_start	-0.022*** (0.006)	weekly_sin1	0.010*** (0.001)
lag1_log_no2	0.764*** (0.001)	I_trial_end	-0.001 (0.010)	weekly_cos1	-0.022*** (0.001)
toll_s1	0.378*** (0.007)	I_perm_start	0.024*** (0.006)	weekly_sin2	0.010*** (0.001)
toll_s2	0.427*** (0.003)	I_price_hike_1	-0.018*** (0.003)	weekly_cos2	-0.003*** (0.001)
toll_s3	-0.004 (0.005)	I_price_hike_2	-0.074*** (0.006)	annual_sin1	0.019*** (0.001)
toll_s4	0.557*** (0.005)	posttime_trial_start	0.000 (0.000)	annual_cos1	0.012*** (0.001)
toll_s5	0.242*** (0.004)	posttime_trial_end	-0.000*** (0.000)	annual_sin2	-0.003*** (0.001)
wind_speed	-0.028*** (0.000)	posttime_perm_start	0.000*** (0.000)	annual_cos2	-0.004*** (0.001)
GDP_growth	0.002*** (0.000)	posttime_price_hike_1	-0.000*** (0.000)		
Pop_over15	0.000*** (0.000)	posttime_price_hike_2	0.000*** (0.000)		
I_covid	-0.015*** (0.004)				
				R-squared	0.826
				Adj. R-squared	0.826
				N	582099
				Std. Err.	0.303

Std. errors (Newey–West) in parentheses; *p<0.1; **p<0.05; ***p<0.01

(2)

ITS Spline Regression (df=6; HAC(24) SE)

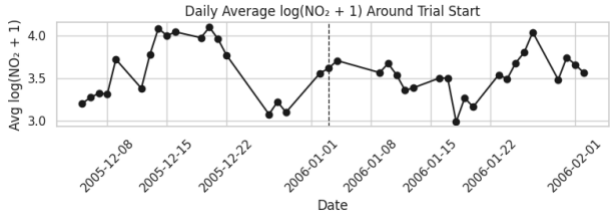
Dep var: log(NO₂ + 1)

(1)		(2)		(3)	
Intercept	0.508*** (0.006)	I_trial_start	-0.032*** (0.006)	weekly_sin1	0.011*** (0.001)
lag1_log_no2	0.772*** (0.001)	I_trial_end	0.001 (0.009)	weekly_cos1	-0.022*** (0.001)
toll_s1	0.508*** (0.006)	I_perm_start	0.023*** (0.006)	weekly_sin2	0.011*** (0.001)
toll_s2	-0.286*** (0.002)	I_price_hike_1	0.002 (0.003)	weekly_cos2	-0.002*** (0.001)
toll_s3	0.824*** (0.006)	I_price_hike_2	-0.079*** (0.006)	annual_sin1	0.018*** (0.001)
toll_s4	-0.160*** (0.003)	posttime_trial_start	0.000 (0.000)	annual_cos1	0.011*** (0.001)
toll_s5	0.174*** (0.004)	posttime_trial_end	-0.000*** (0.000)	annual_sin2	-0.004*** (0.001)
toll_s6	-0.085*** (0.005)	posttime_perm_start	0.000*** (0.000)	annual_cos2	-0.006*** (0.001)
toll_s7	0.041*** (0.004)	posttime_price_hike_1	-0.000*** (0.000)		
wind_speed	-0.026*** (0.000)	posttime_price_hike_2	0.000*** (0.000)		
GDP_growth	0.001*** (0.000)				
Pop_over15	0.000*** (0.000)				
I_covid	-0.013*** (0.004)				
				R-squared	0.828
				Adj. R-squared	0.828
				N	582099
				Std. Err.	0.301

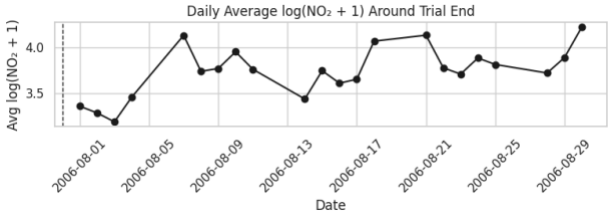
Std. errors (Newey–West) in parentheses; *p<0.1; **p<0.05; ***p<0.01

Figure D.2: Daily Average: Trial Start (1), Trial End (2), Perm Start (3), Hike 2 (4)

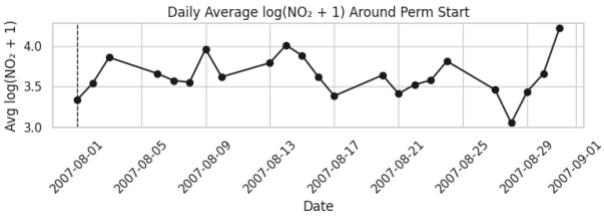
(1)



(2)



(3)



(4)

