Green AI in Industry

Quasi-Experimental Evidence from the Water Treatment Sector*

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Abstract

This paper studies the environmental effects of the large-scale deployment of AI-driven control systems across French wastewater treatment plants operated by a global leader in water supply services. Exploiting quasi-experimental variation in both the timing of adoption and outages, we estimate the causal impact of AI on energy use and carbon emissions. We find that AI allowed treated plants to reduce their electricity consumption and carbon emissions by 5.4% and 6% respectively, and electricity costs by 8.2%, resulting in negative abatement costs, while still improving water effluent quality. The additional electricity demand generated by AI servers represents less than 1% of these savings. Beyond these effects, AI-equipped plants prove more resilient to high operational stress during extreme meteorological events and chemical pollutant peaks. They also improve load management by reallocating electricity consumption from peak to off-peak hours. Finally, we use the DICE model to assess the aggregate implications of our findings in three diffusion scenarios. We find substantial global welfare gains from the CO_2 reductions associated with this industrial AI use case.

JEL: Q53, Q55, O33, L95, Q40. **Keywords:** Artificial Intelligence, Energy Efficiency, Green AI, Digital Twins, Industrial Decarbonization, Abatement Cost, Wastewater Treatment.

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1 Introduction

The growing adoption of generative artificial intelligence (AI) is often cast as a threat to decarbonization: frontier model development has sharply increased the electricity consumption and emissions of data centres, raising concerns about its environmental cost (IEA, 2026; Bonfiglioli et al., 2025; Lawson et al., 2026). Training and inference of general-purpose models are the main drivers of this growth. This framing, however, tends to overlook the energy-saving potential of domain-specific AI, which is attracting growing investment and research attention. Such models are typically smaller and trained on specific data, making them cheaper to run (Luccioni, Jernite and Strubell, 2024), while potentially delivering efficiency gains when embedded in production processes. Whether they may yield a significant environmental benefit is therefore a question that requires netting the energy consumed by AI systems against the operational savings they generate.

This paper provides the first causal, micro-level estimate of the *net* energy and emissions balance of AI adoption in industry. Specifically, we examine the environmental benefits of a pioneer large scale deployment of AI-driven digital twins that actively control aeration across French wastewater treatment plants, operated by a Fortune 500 company and global leader in the water and environmental industry. The AI system combines high-frequency sensors and metering data (at up to 15-minute intervals) with weather forecasts, electricity tariffs, and laboratory samples, to predict treatment requirements and dynamically adjusts aeration subject to effluent-quality constraints.

The setting is well-suited to answering our question. Wastewater treatment accounts for roughly 1.3% of global greenhouse gas emissions[1] and aeration during the secondary treatment phase alone typically accounts for roughly half of a water treatment plant's total electricity consumption. Aeration is also a canonical case of the inefficiency that predictive control can eliminate: it is highly electricity-intensive, treatment requirements fluctuate at high frequency, and insufficient aeration entails large compliance costs, so conventional rule-based controllers maintain large precautionary safety margins. This case study is representative of a wide category of energy-intensive industrial processes that operate over flexible durations, where predictive AI-based optimization using granular data can unlock significant efficiency gains. Indeed, digital twins operating using machine and deep learning models are increasingly deployed in the industry as they can control complex processes and optimize their resource use in energy-intensive activities such as water treatment.

Our empirical strategy combines two sources of quasi-experimental variation: the stag-

[1]This order of magnitude is comparable to aviation, at 1.9% (Ritchie, 2020).

gered roll-out of the system across more than 200 plants, and unplanned interruptions of AI control within plants. Our analytical sample covers 164 plants observed from January 2022 to July 2025. The scale of the deployment is itself noteworthy: in 2025, only about 4% of European utility and manufacturing firms used AI to automate workflows and decision-making (Eurostat, 2025*b*). To our knowledge, it is the first academic study of an at-scale industrial AI deployment and the first study to provide an empirical estimate documenting a net positive energy balance associated to AI. We use both the staggered roll-out and the unplanned interruptions of the system across plants as a quasi-natural experiment to evaluate the overall energy balance of using AI to monitor wastewater treatment, factoring in AI's own energy consumption.

Our main finding is that, for a plant operating under full AI control, electricity consumption falls by 5.4%, electricity-related CO_2 emissions by 6.0% and electricity expenditure by 8.2% on average across the first ten post-activation weeks. Under our costing assumptions, the system pays for itself in energy savings, the implied abatement cost is negative: approximately −€6,300 per tCO_2. In addition, effluent quality does not deteriorate; if anything, compliance with regulatory norms improves. Crucially, the direct upstream electricty consumption of AI amounts to less than 1% of these gains, and a broader, conservative lifecycle accounting, which incorporates incremental hardware and deployment, still yields positive net emissions savings. We then unpack the mechanisms. The gains are concentrated in initially inefficient operating regimes, particularly at low inflows, where fixed-rule over-aeration is the most severe. AI disproportionately reduces electricity use primarily during peak-price hours, generating savings on the expenditure margin beyond pure volume effects. Finally, AI improves the plant resilience to adverse shocks such as extreme rainfall and pollution peaks, by making aeration more state-contingent: the system anticipates or responds rapidly to shocks while avoiding a uselessly prolonged reaction normally induced by fixed-rule control. More generally, AI proves particularly effective in managing nonlinear processes that require intertemporal coordination or the balancing of competing operational constraints.

To gauge the aggregate significance of our micro-level estimates, we embed the estimated energy-efficiency and emissions effects in the DICE climate-economy model. Across three increasingly broad diffusion scenarios, the resulting reductions in climate damages and energy expenditures generate substantial global welfare gains, although the broader scenarios are necessarily extrapolative. Applying the estimates globally to wastewater treatment yields modeled welfare gains of approximately $149 billion, rising to $1.8 trillion when the scope is extended to a limited set of industrial processes for which related control systems have already been developed.

This paper contributes to a nascent literature on the environmental costs and benefits of AI. Existing assessments, largely conducted by international institutions, document the growing energy footprint of AI systems at the macro level and the uncertainty of its aggregate environmental impact (Bogmans et al., 2025; Burian and Stalla-Bourdillon, 2025; IEA, 2025*a*). We complement this perspective by studying a distinct, micro-founded channel through which AI may affect energy use: machine-learning-based process control that optimizes the energy efficiency of industrial operations. Hence, treating AI as a single and homogeneous technology obscures critical heterogeneity between general-purpose and specialized control technologies. In computer science, Schwartz et al. (2020) coined the expression "Green AI", to describe systems whose performance gains that do not come at rising computational cost, and ideally reduce it. We import this concept into the economic literature to frame circumstances under which AI can plausibly contribute to decarbonization, particularly in energy-intensive industrial settings.

Second, we contribute to a small but growing body of micro-econometric evidence on AI and energy use. Sectoral assessments discuss AI's potential to support climate action (see e.g. Rolnick et al., 2022; Stern et al., 2025; Yussuf and Asfour, 2024). Yet, to our knowledge, only two studies provide causal micro-econometric evidence. Metcalfe et al. (2026) investigate AI's effect in households, focusing on EV charging, and find significant reallocation effects but no overall reduction in energy demand. Luo, Wang and Chen (2025) document that exposure to AI-related policy incentives is associated with improvements in corporate energy efficiency, without identifying the underlying operational mechanisms. Moreover, both papers connect only indirectly to the Green AI perspective in the sense that neither provides a comprehensive accounting of AI's *net* energy footprint or climate benefits.

Third, the paper also connects to a growing literature using laboratory, field, and quasi-experimental evidence to study the productivity impacts of AI. Recent causal studies document sizable task-level productivity gains in knowledge work, including customer service (Brynjolfsson, Li and Raymond, 2025), professional writing (Noy and Zhang, 2023), coding (Peng et al., 2023; Cui et al., 2025), and consulting (Dell'Acqua et al., 2023). Industrial operations, by contrast, remain largely absent from this evidence base, despite the fact that industrial processes are both highly energy-intensive and particularly well-suited to data-driven optimization.

Thus, the existing literature on AI and energy leaves two important gaps. First, no empirical study measures the net energy impact of AI adoption, accounting simultaneously for the energy consumed by AI systems and the operational energy savings they generate. Second, most existing evidence relies on proxies or aggregate indicators, with little direct observation of energy use at the level of production processes. This paper bridges these gaps by providing a firm-level, multi-site assessment of the net energy impact of AI adoption within a major industrial group. Using detailed operational and metered data, we quantify both the electricity consumption attributable to AI systems and the energy savings and emissions reductions generated through AI-driven process optimization. This setting offers a unique opportunity to evaluate the environmental consequences of AI in a real-world industrial context, at a scale rarely observed in the literature. By combining micro-level operational data with a comprehensive assessment of the firm's total energy footprint, we deliver an integrated evaluation of AI's net energy and emissions effects within a large industrial organization. In doing so, this paper makes three key contributions: (i) it provides causal, micro-level evidence on the energy consequences of AI adoption, (ii) it offers the first empirical quantification of the net energy balance of a so-called "Green AI", and (iii) it extends AI and energy research to the industry, a critical but understudied sector for AI economics.

The remainder of the paper is organized as follows. Section 2 describes the institutional setting and the AI control system. Section 3 presents the empirical strategy, and Section 4 describes the data. Section 5 presents our main findings, namely the average treatment effects, the implied abatement costs, and the net environmental balance of AI deployment. Section 6 focuses on three operational margins: intraday load shifting, resilience to extreme rainfall, and effluent-quality management under chemical stress. Section 7 assesses the aggregate implications of our findings for global climate and welfare using the DICE climate-economic model. Section 8 concludes.

2 Context and Institutional Setting

This section provides background on the technology and the industry setting we study. We first describe how AI-based control systems deployed as digital twins are used to optimize industrial operations with energy cost reduction objectives. We then summarize key facts about wastewater collection and treatment, with an emphasis on the energy intensity of the treatment processes. Next, we explain why the aeration process in wastewater treatment plants, which accounts for the majority of energy consumption, has significant potential for AI control. We then describe the digital-twin solution adopted by the company for its wastewater treatment plants (WWTPs). Finally, we outline the staggered roll-out that generates the variation exploited in our empirical analysis.

2.1 AI and Digital Twins for Energy Management

AI can extend the scope of traditional information and communication technologies in the optimization of complex systems. In industrial settings, the main promise of AI lies in its ability to combine high-frequency sensor data with predictive models to adjust operations dynamically, thereby increasing process efficiency and flexibility. Digital twins are one of the most prominent AI implementations in industry. They consist in a virtual representation of a physical asset or process that is continuously updated using real-time data and is used to simulate, predict, and optimize system behavior (Fuller et al., 2020; Abdessadak et al., 2025; IBM, 2024). Their modeling layers can combine physics-based models with statistical and machine learning techniques. To date, their applications span various fields, including aerospace, healthcare, manufacturing, utilities, retail, construction, and agriculture (Attaran and Celik, 2023). In practice, they are used to optimize performance, predict failures and schedule maintenance, and evaluate counterfactual scenarios without disrupting production, as real-time feedback supports continuous model updating and learning.

The industrial sector is frequently highlighted as a domain in which AI-enabled optimization could deliver meaningful energy savings and emissions reductions, though the scalability of such gains remains uncertain. IEA (2025*a*) estimate, for instance, that under a scenario of widespread AI adoption, the industrial sector holds the largest abatement potential by 2035, with more than 750 Mt CO_2 avoided in this sector alone. Yet these projections rest on aggregate modelling instead of micro-founded evidence of efficiency gains in actual deployments. Whether such potential translates into real-world outcomes remains an open empirical question.

2.2 Key Facts on Wastewater Treatment Plants

Process overview and the central role of aeration. A WWTP treats wastewater from households, industrial sources, and stormwater before discharge to the environment. In Appendix Section A, we present a diagram and an aerial photo of a WWTP. Treatment proceeds in multiple stages. Preliminary treatment removes large debris through screens and grit removal. Primary treatment then relies on settling or flotation to remove suspended solids. Secondary treatment biodegrades organic matter using microorganisms. Like most plants in Europe, the plants in our setting operate with activated sludge systems. In those processes, wastewater is aerated to provide oxygen to bacteria, which consume organic pollutants. Aeration is essential because it provides dissolved oxygen used by aerobic bacteria to sustain the biological degradation reactions that drive pollutant removal. Some plants also operate tertiary processes to meet more stringent effluent-quality standards, including filtration, nutrient removal, chemical treatment, and disinfection. Secondary treatment, and in particular aeration in activated sludge systems, is the most electricity-intensive component of plant operations (IEA, 2017; US DoE, 2017). The optimal aeration problem is therefore inherently dynamic: it depends on future influent characteristics, process conditions, regulatory constraints, and short-run environmental shocks such as heavy rains.

Energy demand of wastewater treatment. Wastewater treatment is a major contributor to electricity demand. In the US and Europe, almost all WWTP of significant size engage in both primary and secondary treatment (Eurostat, 2025*a*; EPA, 2022). The IEA (2017) provides a systematic assessment of energy use across the water sector and estimates that the sector consumed roughly 120 million tons of oil equivalent in 2014, with electricity accounting for around 60% (about 820 TWh). In particular, wastewater treatment is widespread around the world. It currently accounts for around 0.35 - 1.1% of global electricity consumption (Magni et al. 2025), or roughly 200 TWh in 2014, comparable to the consumption of a mid-sized country like Turkey (IEA, 2017). In high-income regions where wastewater treatment is widespread, it can account for a large share of the electricity consumed by the overall water sector.

2.3 AI-Based Control in Wastewater Treatment

Why WWTPs are a natural environment for AI control. WWTP operations rely on high-frequency sensor data, nonlinear process dynamics, multiple constraints tied to effluent-quality regulation, and substantial energy costs concentrated in a small number of controllable components (notably aeration blowers). Operators have long depended on industrial automation and human oversight, typically implementing rule-based logic triggered by thresholds. While robust, threshold-based control often compresses information into a small set of indicators and may fail to exploit the richness of available data, especially when operating conditions change rapidly (for instance during stormwater inflow events). AI-based control can draw on a larger information set to precisely adjust aeration cycles while maintaining treatment quality, by predicting the water pollution load and then accurately calculating the operation of aerators according to this load, taking into account peak and off-peak electricity prices.

The digital twin solution for WWTPs. Our setting focuses on Veolia Water, a subsidiary of the conglomerate Veolia, which is a global leader in Environmental Services and a Fortune 500 company[2]. It has adopted a digital twin solution developed by the French startup Purecontrol. The solution requires, at a minimum, four models to function: estimation of influent pollution loads, dry-weather inflow estimation, impact of weather forecasts (particularly rainfall), and power disaggregation. The modeling strategy

[2]Hereafter referred to by its brand name "Veolia".

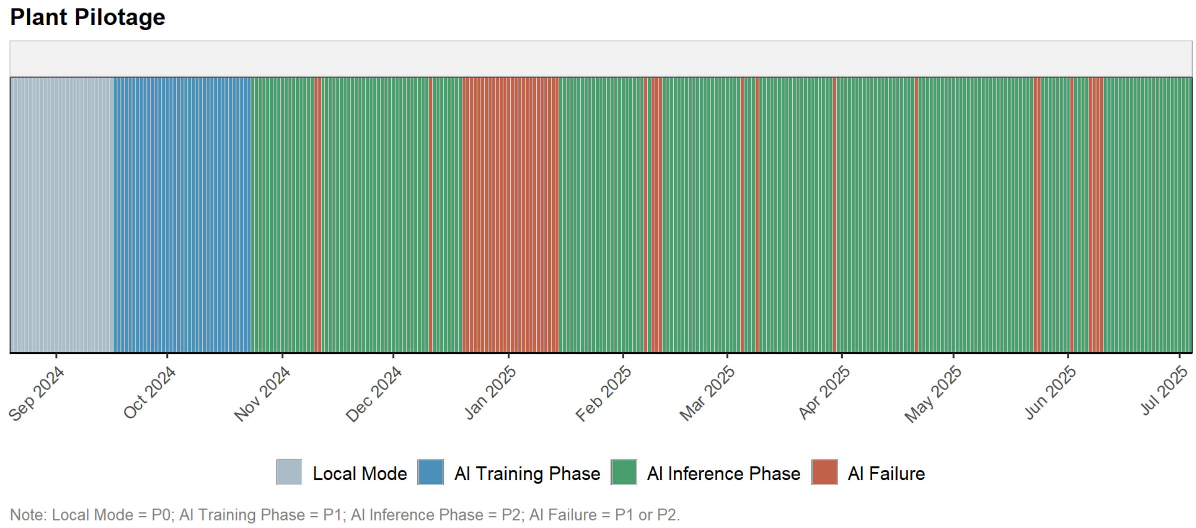
is primarily based on machine learning techniques using non-linear models such as spline optimization, time-series decomposition, and neural networks, alongside linear regression models. Additional models, such as physical models, can be deployed depending on each plant's specific characteristics.

The system optimizes aeration timing and intensity to minimize electricity costs subject to operational and effluent quality constraints. This set-up is aimed at reducing blower operating hours and shifting aeration cycles toward off-peak electricity periods. The solution is designed to integrate with existing industrial automation. It includes (i) a real-time monitoring interface for plant staff, (ii) a prediction layer for variables relevant to treatment dynamics, (iii) real-time tracking of energy consumption by equipment and consumption profiling, and (iv) an execution layer that transmits optimized setpoints to the plant's automation system. Inputs combine internal data (e.g. redox or dissolved oxygen measures, flow rates, manual pollutant measurements) with external information (e.g. electricity tariffs, weather forecasts, and grid carbon intensity).

2.4 AI Deployment and Rollout

Implementation stages within a plant. Deployment of the AI system in wastewater treatment plants follows a multi-stage process. Plants initially operate in "local mode" (P0), relying on on-site automation and pre-defined management thresholds. Aeration is governed by controllers activating actuators based on fixed setpoints, for instance, maintaining dissolved oxygen above a given concentration regardless of incoming organic load. These thresholds are set during plant commissioning and rarely updated, meaning the system cannot respond dynamically to diurnal cycles, seasonal variations, or shock loads. As a result, plants routinely aerate beyond biological needs, wasting energy while still risking compliance failures during peak stress events. Once connected to the AI platform, they transition to an intermediate stage referred to as "AI Training Phase" (P1), which typically lasts around two to three month. During this phase, operations remain broadly similar to local mode, but threshold-setting and calibration are performed centrally by the AI company using data streams from the plant, allowing the AI models to be progressively fine-tuned. This training phase allows to primarily collect data for model calibration, and its duration varies with plant complexity and the speed at which the digital twin converges to actual plant behavior. The final stage, "AI implemented" (P2), represents full AI deployment: the system actively manages plant operations by modeling optimal behavior to minimize electricity costs while satisfying regulatory constraints. Figure 1 illustrates the typical implementation timeline for a plant. In the figure, "AI Failure" denotes episodes in which the plant reverts to P0 or P1 control following AI deployment; the underlying causes are discussed in the next paragraph. Appendix Figure B.1 shows, for the same plant, the sequence of control modes (P0, P1, P2) and the time-varying authorization granted to the AI operator to manage the aeration process.

Figure 1: Adoption Timeline of a typical plant



Notes. This figure plots the daily distribution of AI between phases for a typical facility in our sample from August 2024 to April 2025. AI Inference Phase starts in late October 2024.

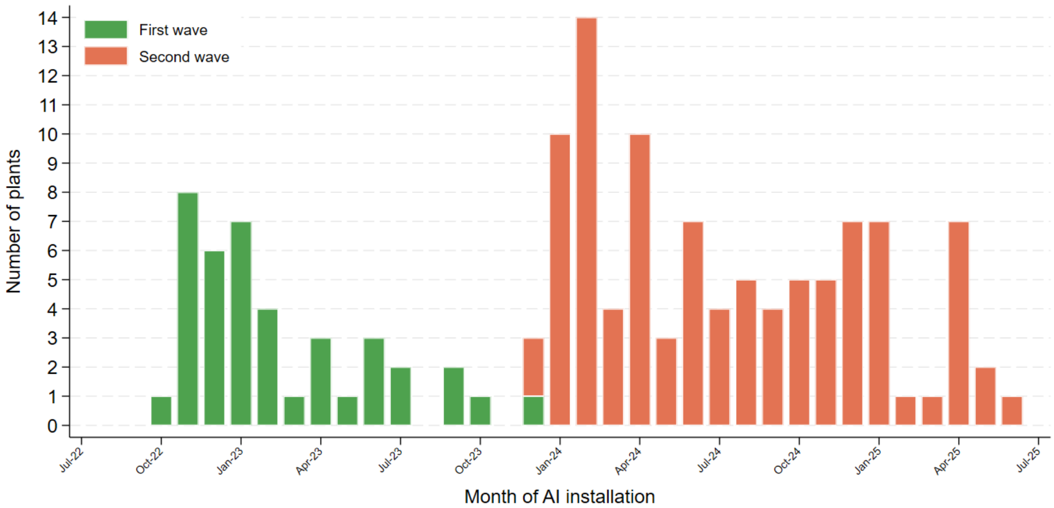
Non-absorbing exposure and operational interruptions. AI operation is not an absorbing state in our context[3]. Plants can temporarily revert from "AI on" to "AI off" for several reasons. These interruptions can be deemed plausibly exogenous to local staff (e.g. connectivity outages), while others are partly endogenous (e.g. prolonged gaps in required manual sampling or deliberate managerial deactivation). Our data allow us to distinguish between (i) interruptions in which AI remains authorized to pilot but cannot operate (e.g. technical failures) and (ii) explicit deactivations in which authorization is turned off. We propose a robustness check eliminating partly endogenous deactivations from the sample, and show it does not affect the results.

Company-wide rollout. The company implemented the system in multiple waves. Figure 2 presents the timeline of AI adoption across plants. In a very early pilot phase, two plants were selected to test the AI system. A first deployment wave then targeted 50 plants, with recruitment beginning in March 2021 and the first AI activation occurring in October 2022. A second, larger-scale wave was launched in November 2023, with Veolia setting an objective of approximately 500 plants. As of July 4, 2025, the end of our observation period, 204 plants in this second wave had already had AI switched on, and 25 additional ones were in the training phase (P1). Across both waves, we recover data for 283 plants in total, of which 183 were AI-managed by the end of the period. Our analytical sample is restricted to 164 plants (of which 139 were AI-managed at the end of the period), as the main variables of interest are not available for all sites. Each plant

[3] In econometric terms, an "absorbing" (or staggered) treatment is one that, once adopted, cannot be exited (de Chaisemartin et al., 2022).

might have one or multiple basins[4].

Figure 2: AI adoption across plants



Notes. This figure plots the number of plants adopting AI each month, distinguishing between the two main adoption waves.

Appendix Figure B.2 plots the number of plants observed in our database over time (regardless of operating mode): plants are differentiated according to AI installation status (in (a)) and AI operating mode (in (b)). While both series increase steadily, the aggregate deployment measure masks within-plant dynamics, as plants may experience intermittent interruptions that temporarily suspend AI operation.

The general eligibility conditions required plants to have a nominal capacity included between 10,000 to 50,000 population equivalents (PE) and to use activated sludge technology.[5] Plants below this threshold were excluded on the grounds that AI installation was not deemed profitable, while plants above 100,000 were managed through AI systems developed internally by Veolia, which were given preference over Purecontrol's solution. Within the eligible capacity range, Veolia operates approximately 500 plants in Metropolitan France, all of which are expected to be AI-managed by the end of the second wave. Plants volunteered for participation and were selected based on compatibility with technical requirements, including the availability of suitable automation interfaces.[6] Plants

[4]While a plant may consist of multiple basins, AI may be installed and operating only on one. However, for simplicity, we aggregate data at the plant level for our analysis, as basin-level data is unavailable for most plants. To the extent that this aggregation assigns treatment status to only partly treated plants, it should only bias our estimates downwards.

[5]In the initial phase, a small number of plants operated under different technologies and sizes. Priority was given to activated sludge plants as this was a more standardized technology allowing for faster deployment. Toward the end of the second wave, a few plants with a nominal capacity between 50,000 and 100,000 PE were also admitted into the scheme.

[6]Some connectivity requirements exist in order for the plant to be eligible, but according to company staff, almost all plants in the relevant capacity range satisfied the connectivity condition. Process mea-

included in the initial wave were those for which AI could be installed without any modification to the existing IT infrastructure. Subsequently, the selection order among volunteer plants was quasi-random, subject only to the constraint that plants within each sub-wave were evenly distributed across French regions.

3 Empirical Strategy

3.1 Variable Definitions

Outcome variables. Our outcomes capture the energy and environmental footprint of plant i over period t. We focus on: (i) electricity consumption, (ii) electricity expenditure, (iii) CO_2-equivalent emissions.

Let $E_{i,h}$ denote electricity consumption (in kWh) for plant i in hour h, and let $P_{i,h}$ denote the plant- and hour-specific electricity price. For any period t (e.g., day or week) consisting of hours $h \in \mathcal{H}(t)$, we define:

$$E_{i,t} = \sum_{h \in \mathcal{H}(t)} E_{i,h}, \tag{1}$$

$$\text{Expenditure}_{i,t} = \sum_{h \in \mathcal{H}(t)} P_{i,h} E_{i,h}. \tag{2}$$

Unlike physical consumption, expenditure reflects both total usage and the timing of electricity use across hours (e.g., shifting load to off-peak periods).

Finally, we compute CO_2-equivalent emissions by weighting hourly consumption by the grid emissions factor κ_h:

$$CO_2 e_{i,t} = \sum_{h \in \mathcal{H}(t)} \kappa_h E_{i,h}.$$

Because κ_h is driven by the external generation mix, we interpret estimates on $CO_2 e$ as reduced-form effects that combine operational responses with exogenous variation in the grid.

Treatment variables: AI exposure as a non-absorbing intensity. Our treatment design is non-standard in two respects. First, exposure is non-absorbing: even after installation, AI can stop operating due to connectivity outages, missing required manual inputs, or managerial deactivation. Second, the treatment intensity is continuous because AI can be used a fraction of time during the day.

We construct the three following treatment measures. For each plant i and period T,

surement requirements include real-time flow measurement, at least weekly measurements of NH_4 and NO_3, and sensors for redox potential or dissolved oxygen.

let $D_{i,T}$ denote the (continuous) intensity of AI use. We consider: (i) the intensity $D_{i,T}$ itself; (ii) an indicator for any exposure $\mathbb{1}\{D_{i,T} > 0\}$; and (iii) an "installed" indicator, equal to one once AI has operated at least once at plant i, regardless of whether it is active in period T, i.e. $\mathbb{1}\{\sum_{t=0}^{T} D_{i,T} > 0\}$. This last measure is an absorbing state, i.e. that never reverts back to zero. Hereafter, we call these three indicators respectively: *AI usage*, *Treated* and *AI installed*. Unless otherwise specified, our baseline specification relies on the continuous treatment intensity $D_{i,t}$.

3.2 DID estimators for non-binary non-absorbing treatments

The canonical TWFE estimator is subject to well-known biases under treatment-effect heterogeneity, notably contamination from already-treated units and negative weighting of cohort-specific treatment. While economists long believed that the parallel trends assumption was the only requirement for TWFE to deliver a causal estimate in staggered adoption designs, the recent difference-in-differences literature has shown that TWFE regressions yield consistent estimates only under strong homogeneity assumptions, and may be biased when treatment effects vary over time or across adoption cohorts (de Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Goodman-Bacon, 2021; Borusyak, Jaravel and Spiess, 2024). This concern is salient in our setting, where learning-by-doing may generate larger effects for later exposure spells or later-treated cohorts. Our core estimates rely on the robust DID estimator of de Chaisemartin and D'Haultfoeuille (2024). We additionally report TWFE results when analyzing fixed structural differences (e.g. peak versus off-peak hours), where TWFE provides a valid and transparent decomposition that the DCDH estimator is not designed to deliver.

Most staggered DID estimators and commands are designed for binary treatment variable and absorbing adoption patterns. In contrast, our setting features a non-absorbing treatment with repeated treatment status changes, as well as a potentially non-binary (discrete or continuous) treatment intensity[7]. We therefore rely on the heterogeneity-robust DID estimators for dynamic effects from de Chaisemartin and D'Haultfoeuille (2024). These estimators are explicitly designed to accommodate treatments that may change over time, and to remain valid under treatment-effect heterogeneity where standard two-way fixed effects can be biased.

[7]Treatment intensity varies not in terms of quality, but in terms of daily share of time. In our setting, the treatment variable is binary or not depending on whether we simply adopt a dummy variable or the *AI usage* variable.

DID estimator for continuous and non absorbing treatment. Let i index plants and define the first time the plant's exposure changes:

$$F_i = \min\{t \geq 2 : D_{i,t} \neq D_{i,t-1}\}.$$

where $D_{i,t}$ is the treatment status of unit i at time t.

For horizon $\ell \geq 1$, define the control set of "not-yet-changed" plants sharing the same baseline exposure $D_{i,1}$:

$$\mathcal{C}_{i,\ell} = \{j : D_{j,1} = D_{i,1},\ F_j > F_i - 1 + \ell\}.$$

In our setting, all plants except one start from a common baseline exposure $D_{i,1} = 0$, i.e. no plant has AI activated at the beginning of the sample period. This ensures that the control set $\mathcal{C}_{i,\ell}$ is well-defined and non-empty for all switchers, and that comparisons across units are not contaminated by heterogeneous pre-treatment exposure levels.

The plant-specific event-study DID is:

$$DID_{i,\ell} = \left(Y_{i,F_i-1+\ell} - Y_{i,F_i-1}\right) - \frac{1}{\#\mathcal{C}_{i,\ell}} \sum_{j \in \mathcal{C}_{i,\ell}} \left(Y_{j,F_i-1+\ell} - Y_{j,F_i-1}\right).$$

Averaging across switchers observed at horizon ℓ yields DID_ℓ. We then aggregate these horizon-specific estimates into an Average Cumulative Total Effect (ACTE):

$$ACTE = \frac{1}{L} \sum_{\ell=1}^{L} \widehat{DID}_\ell$$

which averages treatment effects uniformly across the L post-treatment horizons.

The estimator relies on (i) no anticipation, (ii) no interference, and (iii) a parallel-trends assumption for the relevant counterfactual "status-quo" outcomes, conditional on fixed effects and controls[8]. Under this set of assumptions, this estimator is equal to the expected difference between i's actual outcome at $F_{i-1+\ell}$ and its counterfactual "status-quo" outcome:

$$\delta_{i,\ell} = \mathbb{E}[Y_{i,F_i-1+\ell} - Y_{i,F_i-1+\ell}(D_{i,1}...D_{i,1}) \mid \mathbf{D}]$$

with $\mathbf{D} = \big((D_{i,1}, \ldots, D_{i,T})\big)_{i=1}^{N}$ a vector stacking the treatments of all plants at every

[8]The estimator only compares switchers and non-switchers with same period-one treatment, whereas the "naively-extended" Callaway and Sant'Anna (2021) estimator compares switchers and non-switchers with different period-one treatments, thus relying on an unconditional parallel trends assumption for status-quo outcome.

period. Accordingly, the ACTE can be interpreted as the average effect of AI adoption on treated plants on each period over the post-treatment window.

We report placebo (lead) estimates in an event-study plot to assess the plausibility of assumption (iii). Assumption (i) can be tested by comparing plant behavior before and after notification of future treatment. Lastly, we expect Assumption (ii) to hold given the nature of our setting. Wastewater allocation to different plants is fixed by infrastructure design that long pre-dates our analysis. Even if, e.g., managers of treated vs. untreated plants were to interact during the roll-out, the untreated plants' managers cannot utilize the AI technology without installation, which would be observable in our setting.

We estimate the effects of AI by aggregating the data at the weekly frequency for the use of the de Chaisemartin and D'Haultfoeuille (2024) estimator. In this framework, the choice of time aggregation is consequential because the estimator constructs counterfactual outcomes over the same horizon as the unit of observation. While we report results for daily, weekly, and monthly time aggregation, our preferred specification considers weekly data. Monthly aggregation is too coarse as it smooths substantial within-month variation in AI activation into average treatment intensities and reduces the number of identifiable treatment episodes as well as the pool of units that can serve as valid controls. Daily aggregation, by contrast, is subject to more noise as electricity consumption exhibits pronounced intra-week volatility and may obfuscate the benefits of shifting electricity consumption within days of the week. Weekly aggregation preserves meaningful variation in treatment while allowing effects to accumulate over several days. Appendix Section E.2 compares results across alternative time aggregations.

4 Data and descriptive statistics

4.1 Data

Our analysis relies on high-frequency monitoring data from Purecontrol on Veolia wastewater treatment plants under its management, complemented by Veolia administrative data and weather data from Meteo-France. The main variables of interests derived from the Purecontrol database forming our main sample are :

(1) Share of time of each plant is in control mode, measuring the fraction of time during which the plant operates under threshold-based control either by the plant management (P0) or by Purecontrol (P1), and the optimized AI control mode (P2). Control modes are reported as a continuous variable between 0 and 1 at the daily level.;

(2) Electricity active power, observed mostly at a 10-minute resolution and expressed in kilowatts (kW). In the analysis, it is aggregated at the hourly level and converted into

electricity consumption, expressed in kilowatt-hours (kWh);

(3) Carbon footprint of electricity consumption, sourced from RTE's open-access data RTE (2026). This variable captures the CO2-equivalent emissions associated with the plant's electricity use, expressed in $kgCO_2$ and observed at the hourly level.[9]

(4) Hourly electricity prices. As the data typically distinguish only two tariff periods at the day-level, we use this variable to get a peak / off-peak hours indicator, with off-peak hours typically occurring between 10 pm and 5 am (Figure D.7);

(5) Electricity costs (in current €) are reconstructed by computing, at the hourly level, the product of electricity consumption and the corresponding electricity price.

(6) Plant management authorization status. This dummy variable captures whether plant management authorizes Purecontrol to control the aeration process using either AI-optimized mode (P2) or manual mode (P1).

To enrich our primary dataset, we include additional variables which are less commonly available than the three score indicators mentioned above, including:

(7) Nominal capacity, available for most plants and measured in Population Equivalent (PE), which corresponds to the maximum load of organic pollution that the plant is built to handle under standard operating conditions;

(8) Inflow rate, which represents the volume of water treated by the plant, measured in cubic meters (m^3);

(9) Redox, measured in millivolts (mV), which reflects the oxido-reduction potential (ORP) of treated water and is central to aeration control;

(10) Daily average concentrations of ammonium, nitrate, and phosphate, measured at the end of the water treatment process, as well as the plant and time-specific quality thresholds for each variable. All AI-managed plants were required to conduct at least every ten days a test on ammonium and nitrate concentration[10];

(11) Rainfall data from Meteo-France, extracted at the hourly level and matched with plant-level data thanks to plants' geolocation data.

4.2 Summary Statistics

Table 1 presents the summary statistics of the sample, divided into four groups: all plants (All); plants where AI has not been deployed during our sample period yet (Never treated); observations of plants before the first deployment of AI (Treated, pre); and observations after the first deployment of AI (Treated, post). The sample comprises 2.2 million hourly

[9]The emissions factor is national in scope, consistently with the organisation of the French electricity market. One caveat is that it reflects only domestically produced electricity, and therefore does not account for emissions embedded in imports.

[10]Within the week, the day at which the sampling was conducted was not random, but there is no reason to suspect that the pattern of sampling was different before and after AI adoption.

observations on electricity consumption, carbon footprint, electricity prices and the share of time during which AI is used, across 164 plants. Within the sample, approximately one quarter of the plants are never equipped with AI. The sample data spans from January 2022 to July 2025 (Appendix Figure D.1). The first plant began operating under AI control in October 2022. The start date of electricity power measurement varies across plants but typically precedes the adoption of AI-managed (P2) mode by several months[11]. AI is deployed on selected plants through two main deployment waves. Appendix table D.1 provide the summary statistics by adoption wave. There are no major differences between the stations from the two adoption waves, apart from the fact that the stations from the first wave are slightly smaller. In Appendix table D.2 we report summary statistics for the subsample restricted to observations for which all control variables - inflow, rainfall and redox - are available.

Table 1: Summary Statistics

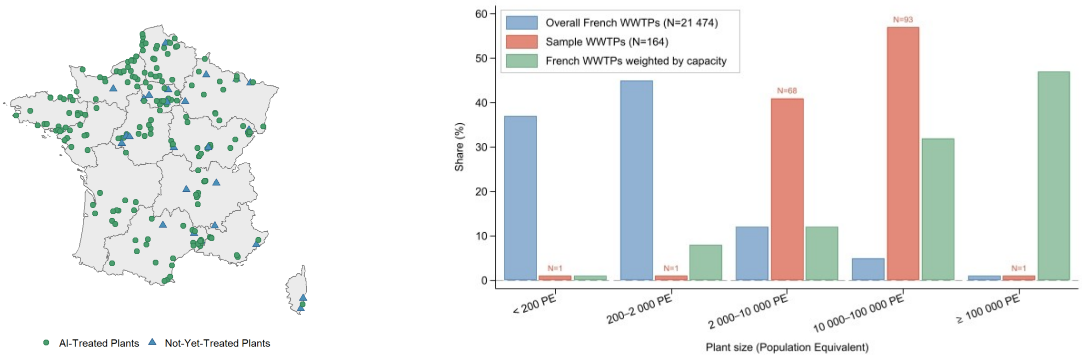
Variable	**All**	**Never treated**	**Treated, pre**	**Treated, post**
Observations	2,242,511	148,211	585,712	1,508,588
Plants	164	25	138	139
Nominal Capacity (PE)	19,804	17,913	20,283	20,144
AI usage (Share of time)	0.39	0	0	0.58
Elec. Consumption (kWh)	66.9	80.4	65.4	66.1
Carbon em. ($kgCO_2e/h$)	1.8	1.9	2.25	1.62
Electricity price (€/kWh)	0.11	0.12	0.09	0.11
Electricity cost (€/h)	7.23	10.4	6.16	7.32

Notes: This table shows summary statitics of our dataset, presenting the number of observations and plants in each group and then the average of the main outcome variables. The first column consists of all plants in our sample, the second column includes plants who never receive coverage by AI. The third column presents statistics for treated plants before they receive AI installation, and the fourth column includes treated plants after the first AI deployment.

Figure 3 displays the geographic distribution and size, measured by nominal capacity in Population Equivalent (PE), of the plants in our sample. Facilities are spread relatively evenly across metropolitan France. As shown in Appendix Section D.2, the sample is heavily skewed toward medium and large plants: while roughly 80% of the 21,474 French WWTPs recorded in 2016 fall below 2,000 PE, only two such plants are included. By contrast, the sample comprises 68 medium-sized plants (2,000 - 10,000 PE) and 93 large plants (10,000 - 100,000 PE), representing 3% and 8% of their respective national categories. This reflects a technical constraint: the AI device is poorly suited to smaller installations. That being said, small plants collectively account for only 9% of total in-

[11]For a plant to get enrolled in the AI-managed system, it needs at least a AI training phase during which Purecontrol teams take control over the plant that is therefore no longer managed locally. It is only when the training phase is completed that the plant gets AI-managed. The duration of this step might vary across plants but typically lasts 2 to 3 months.

stalled capacity nationwide (CGDD, 2019), so their absence from the sample has limited consequences for the representativeness of our estimates in terms of overall wastewater sector footprint.



(a) Plant geographical location

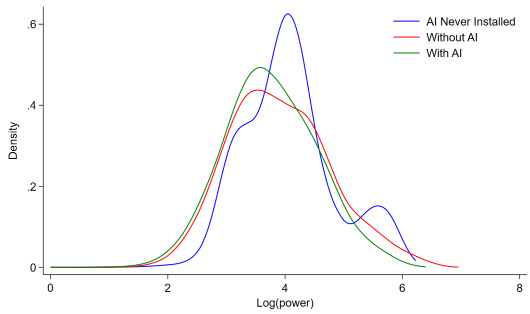
(b) Plant nominal capacity

Figure 3: Plant Location and Nominal Capacity

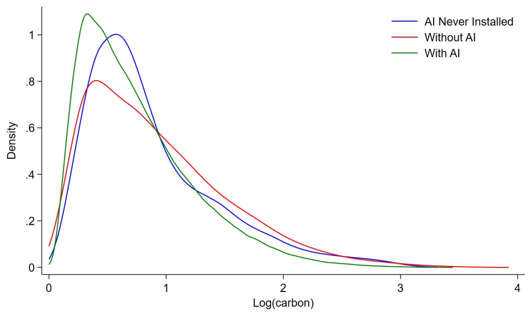
Note: This figure shows the geographical and capacity distribution of plants within our sample. The plant nominal capacity are compared with the French national distribution in 2016 (CGDD, 2019).

In Figure 4, we plot the raw distribution of the main variables of interest, presented in the previous section: the outcome variables (Electricity consumption, Carbon footprint, Electricity cost) of the never-treated group (AI never installed), as well as the treated group when AI is operating (With AI), the treated group before AI installation and when AI is not operating (Without AI), and the explanatory variable (AI control) for treated units. We observe that plants operating with AI consume less electricity and emit less carbon emissions relative to both plants never-treated and plants from the treated group operating without AI. However, AI does not seem to have an impact on electricity costs, but it can be explained by the average increase in electricity prices between pre-treatment and post-treatment periods (Figure D.5) especially during winter (Figure D.6).

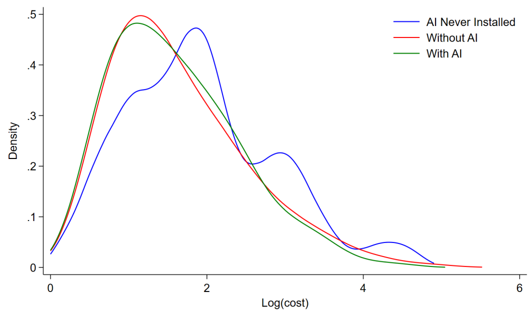
Table 2 presents summary statistics on AI interruptions. Three distinct sources may cause AI to cease operating. Connectivity outages prevent the transmission of plant sensor data to Purecontrol, generating failures that can be considered exogenous to both plant operations and AI performance. In other cases, the nature of the interruption is less clear-cut, as the underlying cause cannot be straightforwardly classified as exogenous, arising either from plant managers' decisions to disable AI management or from the Purecontrol team reverting to manual control (P1). Leveraging data on manager authorization status and the intraday distribution of control modes at the time of failure, we classify interruptions as follows: *unauthorized* when AI management has not been enabled by the plant; *AI-team decision* when local plant control (P0) accounts for less than 10% of the day, indicating that the AI team has assumed manual control for most of that day; and *connection failure* otherwise. As shown in Table 2, the majority of interruptions are



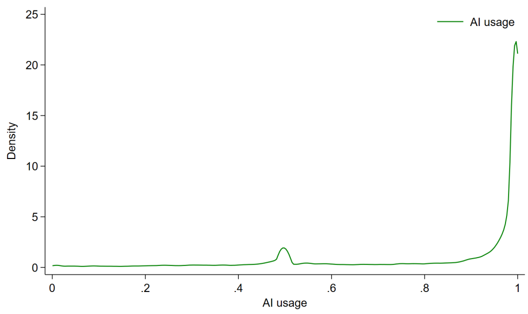
(a) Electricity Consumption (in log kWh)



(b) Carbon Footprint (in log $kgCO_2e/h$)



(c) Electricity cost (in log €/h)



(d) AI control share of time

Figure 4: Distributions of the variables of interest

Notes. Observations for electricity consumption, carbon footprint and electricity costs are at the hour-level, and for AI control at the day-level. The first three variables are expressed in log. "AI Never Installed" refers to never treated plants; "Without AI" refers to observations from plants that have AI installed but where AI control is disabled (either before the first treatment date or after the first treatment date but where AI is not operating); "With AI" refers to observations from plants that will have AI installed when AI is operating.

endogenous: 46% of failure-hours correspond to unauthorized AI management, and 24% reflect deliberate reversions to manual control by the AI team, leaving 30% attributable to exogenous connectivity outages. These endogenous interruptions introduce a potential downward bias in our estimates of the AI treatment effect, insofar as AI is more likely to be disabled precisely in circumstances where plant outcomes would have been unfavorable regardless. We address this concern in the robustness checks of Section 5.2 by restricting the sample to weeks free of potentially endogenous failures.

Table 2: AI interruptions summary statistics

Failure Type	**Frequence**	**Percent**
Unauthorized	206,307	46.11
AI-team decision	107,419	24.01
Connection failures	133,677	29.88
Total	447,403	100.00

Notes. Observations are at the hourly level, restricted to periods of AI failures, after the deployment of AI. The first type of failures correspond to observations where the plant withdrew AI authorization. The second type of failures correspond to hours with any presence of P1 mode (AI team manually overriding the AI). Connection failures capture the residual exogenous failures, attributed to connection outages.

5 Main Results: the net balance of AI use

5.1 Conceptual Framework

To interpret these results and discipline their interpretation, we develop in Appendix Section F a stylized model of an industrial operator facing an asymmetric loss when using an energy-intensive input: undershooting a service target (here, aeration) risks costly non-compliance, while overshooting merely wastes energy. Absent precise information, the operator optimally over-provisions, holding a safety margin against undershoots. Formally, the operator chooses a setpoint below which the risk of a costly undershoot is just balanced against the cost of wasted energy, so the optimal choice solves

$$a^* = F_R^{-1}\big(\tau(p)\big), \qquad \tau(p) = \frac{\psi - p}{\phi + \psi}, \tag{3}$$

where F_R is the operator's predictive distribution of required aeration, p the electricity price, and $\psi > \phi > 0$ the unit costs of undershooting and overshooting[12]. Because $\psi > \phi$, the critical probability τ exceeds 1/2: the operator sets aeration above the median, over-provisioning to guard against non-compliance.

We model AI adoption as an information refinement (a mean-preserving contraction of the predictive distribution of required input), which lets the operator shrink this margin. The model yields five predictions that organize our empirical analysis. First, AI lowers average energy use by reducing the safety margin (Section 5.2, §Overall Impacts). Second, savings concentrate where baseline operations are least efficient, at low inflow (Section 5.2, §Heterogeneity Analysis). Third, AI creates price responsiveness that is absent pre-adoption, enabling intertemporal reallocation toward low-price hours (Section 6.1). Fourth, AI compresses the right tail of the aeration distribution rather than shifting treatment quality, a prediction we test directly on the resilience to adverse shocks such as intense rain episodes (Section 6.2) and effluent quality (Section 6.3). Fifth, because models improve with data, savings accumulate gradually with diminishing returns (Figure 5).

We view the joint confirmation of these five predictions, several of which are non-obvious, as evidence that AI operates through the information channel the model isolates.

[12] We suppress the conditioning on the information set and the plant–time indices for readability; see Appendix F.

5.2 Gross impact

Overall Impacts. Table 3 examines the impact of AI on energy consumption, carbon footprint and electricity costs, measured over 10 weeks using de Chaisemartin and D'Haultfoeuille (2024) . The columns differ in the definition of the measure of AI use. In the column *AI usage*, the treatment variable is the share of the day during which the AI piloting mode is switched on. AI generates energy savings of 5.4 %, reduces the carbon footprint by 6 % and electricity costs by 8.2% on electricity cost assuming AI is switched on 100% of time. In the second column *Treated*, we present the observed effect when AI is switched on at least part of the day. On average, on days where it has been active at least once during the day, AI has generated electricity consumption savings of 3.5%, carbon footprint savings of 4%, and electricity cost savings of 5.5%. Finally, in the third column, the dummy *AI installed* captures the effect of AI installation, irrespective of whether AI is actually switched on. AI installation has generated energy savings of 3%, a carbon footprint reduction of 3.3%, and a reduction in electricity costs of 4.6%. The weaker effect of AI installation is explained by the fact AI is switched off 42% of the time after its installation because of connectivity outages, or unauthorized AI control by the plant managers. Importantly, electricity consumption, electricity costs, and carbon footprint are measured at the plant level rather than at the aeration process level. As a result, when focusing solely on the aeration process, the efficiency gains are approximately twice as large in magnitude, since the aeration represents approximately 50% of the overall plant electricity consumption.

In Figure 5, the event-study graph suggests the absence of detectable pre-trends, followed by a gradual, statistically significant effect in the post-treatment period. The event-study graph shows, for each week relative to treatment, the average observed effect without weighting by the plant's actual intensity of AI use. The effect fully materializes after approximately 8 weeks (roughly two months). While Table 3 uses log values, Appendix Table E.4 also shows results with the absolute values of the effects of AI usage: a full AI usage reduces weekly electricity consumption by 606,8 kWh, electricity costs by €199, 4, and carbon emissions by 22.8 kgCO_2e, on average per plant.

Abatement Costs. To quantify the cost-effectiveness of the technology, we compute an abatement cost that accounts for both the energy savings and the deployment cost of the AI system. The ACTE implies an average weekly energy cost reduction of €199 per plant over the post-treatment window, as stated in Appendix Table E.4. On the cost side, we use the subscription fee negotiated between the operator and the AI provider, averaged across plants in the sample. Assuming that the provider prices at marginal cost[13], and amortizing the fixed component of the contract over a short-term horizon, the

[13] It is a conservative assumption given the structure of the market for this type of software.

Table 3: Effects on weekly electricity consumption, carbon footprint and costs

	AI usage	Treated	AI installed
Electricity Consumption			
	-0.054***	-0.035***	-0.030***
	(0.017)	(0.013)	(0.01)
Carbon footprint			
	-0.060***	-0.040***	-0.033***
	(0.019)	(0.012)	(0.012)
Electricity cost			
	-0.082***	-0.055***	-0.046***
	(0.017)	(0.012)	(0.011)
Observations		13,708	
Number of plants		164	

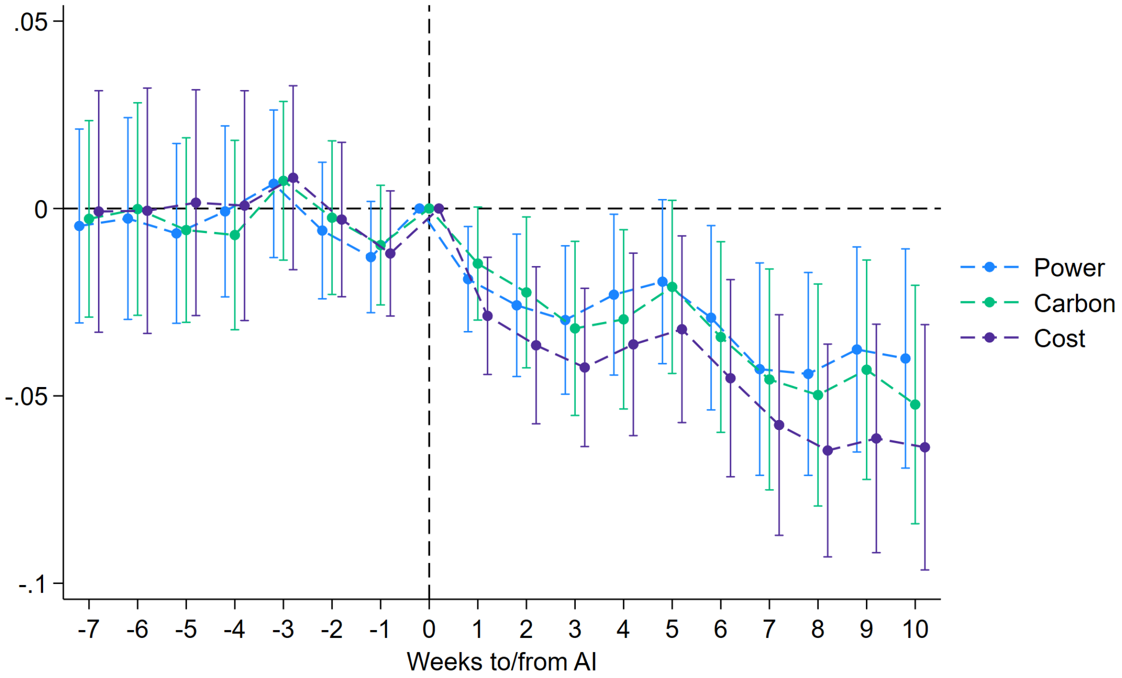
Notes: We report the average cumulative total effect (ACTE) measured over 10 weeks using de Chaisemartin and D'Haultfoeuille (2024). Electricity consumption, carbon footprint, and electricity cost are expressed in log values. The definition of the measure of AI use differs across columns. Effect on electricity cost is obtained controlling for the mean individual weekly electricity price. Standard errors are clustered at the plant level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

net annualized cost of the AI system per plant amounts to approximately €2,800/y[14]. The same computation for carbon emissions gives an average weekly carbon emissions reduction of 22.8 $kgCO_2$ per plant over the post-treatment window. We obtain an implied abatement cost of approximately $-$€$6,342$ per tCO_2. The negative sign indicates that the technology is not only emissions-reducing but also cost-saving net of deployment expenses: operators effectively *save* money while abating carbon. This figure is robust to reasonable variations in the amortization horizon and in the choice of average vs. marginal emission factor. This evidence points toward strongly negative abatement costs for this technology, placing it among the most cost-effective decarbonization levers available to the industry. Energy efficiency measures with negative net abatement costs have long been identified in the literature (Enkvist, Nauclér and Rosander, 2007; Gillingham and Palmer, 2014). Our results suggest that AI-assisted process optimization in water treatment may represent one such "$20 bill on the sidewalk".

Robustness. The causal interpretation of our results rests on a set of identifying assumptions that we probe through a battery of robustness checks, varying the estimation strategy, the treatment definition, and the composition of the sample.

[14]The decomposition of the contract is not disclosed for reasons of commercial confidentiality. We report only an average approximate of the net cost figure in order to compute the abatement cost.

Figure 5: Event study, AI effect



Notes. This figure plots the coefficients and 95% confidence intervals from the event-study regression using de Chaisemartin and D'Haultfoeuille (2024). Dependent variables are in log terms. Effect on electricity cost is obtained controlling for the mean individual weekly electricity price.

1. Alternative estimators. We show similar results using alternative estimators robust to treatment effect heterogeneity. Appendix Figure G.1 presents event-study estimates from the estimator de Chaisemartin and D'Haultfoeuille (2024), alongside a standard TWFE and the estimator of Borusyak, Jaravel and Spiess (2024). We estimate here the effect of the AI installation which constitutes an absorbing treatment. All three specifications present a reduction in electricity consumption of approximately similar to our main estimator in the weeks following installation, with no evidence of pre-trends in the six weeks preceding treatment.

2. Restriction to exogenous failures. To address the potential downward bias in our estimates of the AI effect caused by endogenous failures, we restrict our sample to weeks unaffected by endogenous interruptions. Specifically, we drop all post-installation weeks where AI management was authorized less than 80% of the time, and all weeks where the AI team switched to manual control (P1 mode) more than 20%. This last filter allows us to flag deliberate decisions by the AI team to disable AI rather than a simple connectivity outage. We don't apply this filter in the first two weeks post AI installation as manual interventions in this period are part of the installation process and are not deliberate decisions to disable the AI. In total, we remove 3,383 weeks, representing 36%

of post-installation observations and 24% of the overall sample. The results of the AI effect, reported in Appendix Table G.1, are almost not affected by this restriction: we estimate reductions of 4.4%, 4.9%, and 6.9% in energy consumption, carbon footprint, and electricity cost, respectively, when AI is activated 100% of the time. The effect of AI installation remains statistically significant and broadly consistent with our baseline estimates.

3. Rebound effect. We investigate the source of the differential between the estimates reported in the first, second, and third rows of Figure 5. This gap could stem either from variation in the share of time during which the AI is switched on, or from a rebound effect arising when the AI is switched off. Several mechanisms could generate such a rebound, including less attentive plant management resulting from the delegation of control to the AI, or a gradual erosion of operator skills. We test the rebound hypothesis by regressing electricity consumption, carbon footprint, and electricity costs in a TWFE specification that jointly includes the indicator for AI installation (*AI installed*) and the effective AI piloting share of time (*AI usage*). The coefficient on *AI installed* captures the net effect on each outcome during post-installation periods when AI is not actively piloting, relative to the pre-installation baseline. In some specifications, we additionally control for a dummy flagging weeks classified as endogenous AI failures, following the definition introduced in the previous robustness check[15]. Results are reported in Appendix Table G.2. Without controlling for endogenous failures, we find a positive and statistically significant coefficient on *AI installed* for electricity consumption (+2.8%) and carbon footprint (+3.7%), suggesting a partial rebound effect: when AI is installed but not actively piloting, energy consumption and emissions tend to be higher than in the pre-installation period. Even in this most conservative scenario, the magnitude of the rebound never exceeds half of the overall effect, and the difference between the coefficients remains significantly positive. Once we control for endogenous AI failures, the *AI installed* coefficient becomes statistically insignificant for electricity consumption and weakens markedly for carbon footprint, while the *Endogenous AI failure* indicator is itself positive and significant across all three outcomes. Taken together, these results suggest that the apparent rebound effect documented in the baseline specification is largely driven by periods of deliberate AI deactivation, plausibly unrelated to any genuine shift in the plant's underlying energy demand.

4. Effect across AI adoption wave. We compute the separate effectiveness of AI usage across the two adoption waves. Appendix Table G.3 reports the estimates of AI usage on electricity consumption for each wave separately, using never-treated plants as controls in both subsamples. The average total effect for the second wave is -4.7%, consistent with

[15] That is, weeks in which AI management was authorized less than 80% of the time, together with all weeks in which the AI team switched to manual control more than 20% of the time, occurring more than two weeks after the first treatment date.

our main results. For the first wave, the estimated effect is -6.0% but does not reach the significance levels. In both cases, the joint placebo test fails to reject the null hypothesis of parallel trends. The consistency of the estimates across waves suggests that the baseline results are not driven by a particular adoption cohort.

5. Additional robustness checks. We check that our results are not sensitive to several other changes in specifications. In Appendix Table G.4, we run a Diff-in-diff specification with the addition of an inflow control; the result is unaffected in significance and magnitude. On the contrary, when we add redox as a control, the result remains significant, but the magnitude is smaller; this is in itself consistent with the important endogenous changes in redox values due to AI implementation. In complement, since we observe that the never-treated units had different characteristics in Section 4, in Appendix Table G.5, we check that the restriction of the sample to non-never treated units does not affect our results.

Heterogeneity analysis. We examine the heterogeneity of AI effects according to plant size, water inflow levels, energy intensity, and water oxidation levels using hourly data[16].

1. Plant size, flow amplitude, and energy intensity. We examine size heterogeneity along two dimensions of scale: the size of the plant, measured by nominal treatment capacity, and the effective operating scale, measured by water inflows. We find no evidence that the effectiveness of AI varies systematically with the nominal capacity or the average inflow levels. As shown in Appendix Figure H.1, treatment effects are broadly flat across the capacity distribution, suggesting that AI does not deliver larger gains (in %) in larger installations. By contrast, we observe substantial heterogeneity with respect to absolute inflow levels. When we interact AI use with inflow (measured in logarithm) in specifications analogous to our baseline TWFE model, we find that the energy-saving effect of AI reaches 12.8 and 13.6 percent for electricity consumption and environmental footprint respectively at very low inflow levels (Appendix Table H.1). We also find that energy intensity (measured by the electricity consumption per unit of inflow) decreases sharply as inflow levels rise (Appendix Table H.2), indicating that the water treatment process exhibits strong economies of scale and operates more energy-efficiently at higher flow rates. Appendix Table H.2 also shows that the energy-saving impact of AI diminishes at higher inflow levels, and that AI efficiency gains are most pronounced at low inflow. AI allows improvements of energy intensity up to 19% at very low levels of inflows, and this effect becomes less strong at higher inflow levels. Taken together, these results suggest that AI effectively mitigates the energy inefficiencies that occur at low-operating regimes.

[16]The piloting time is only available at the day-level, so we assume a fixed level of piloting time across hours.

We further examine heterogeneity in AI usage effects according to pre-installation energy intensity. Specifically, we estimate heterogeneous treatment effects by quintile of mean plant energy intensity prior to AI adoption using our baseline TWFE model and report the results in Appendix Figure H.2. We find no significant effect for plants in the lowest energy intensity quintile, while AI usage leads to statistically significant and stable reductions in electricity consumption across the remaining quintiles. These results suggest the existence of a ceiling effect for highly energy efficient plants, which are already operating close to optimal levels, whereas AI generates broadly similar efficiency gains for all other plants.

2. The Oxidation - Reduction Potential (ORP). A key concern is whether AI saves energy by genuinely improving efficiency or by lowering the intensity of the treatment task. To rule out this latest possibility, we examine ORP (redox), a standard indicator of oxygenation conditions and treatment quality. Checking ORP permits to rule out the possibility that AI reduces electricity simply by relaxing treatment (e.g. operating under more reducing conditions that might compromise nitrification or effluent standards). Following the consensus in the technical literature on water treatment, we classify redox values into three standard operating ranges: very low (below -200 mV), moderately anoxic (-200 to 0 mV), and oxidizing (above 0 mV)[17] When we compare the distribution of ORP values by AI treatment status (Appendix Figure D.9), plants with AI spend much more time within this optimal range. This shows that AI does not reduce electricity by relaxing treatment standards. Instead, AI improves process control by keeping the system more consistently in the biologically efficient operating window, achieving both better compliance and lower energy use. We interact the bins with AI use in a TWFE specification (Appendix Figure I.2). The results show strong heterogeneity across redox regimes. AI delivers the largest gains when the biological process is close to binding or unstable conditions. At very low redox levels (below -200 mV), where small timing errors in aeration can generate large energy costs or quality risks, AI substantially improves operational efficiency, yielding energy savings of approximately 20 p.p. In moderately anoxic conditions (-200 mV to 0 mV), where the process is already relatively well controlled, AI delivers more modest but still significant gains (-7p.p). By contrast, when redox values are positive, indicating an already oxidizing environment, there is little room left for optimization, and we find no significant effect.

[17] The water treatment literature identifies a target ORP range between -200 and 0 mV (Luccarini et al., 2017; Cheng, Kumar and Lin, 2012). In particular, values below -200 mV risk poor nitrification (Charpentier et al., 1998; Myers, Myers and Okey, 2006). Conversely, ORP values above 0 mV suggest insufficient anoxic conditions for denitrification. Following discussions with the Purecontrol engineers we exclude data below -450 mV and above 450 mV that are mismeasurements.

5.3 Net environmental balance

What is Green AI? Assessing AI's environmental balance, that is to say jointly evaluating its operational benefits and its own footprint, is both central and technically challenging, and lies at the core of the notion of Green AI (Rojahn and Grum, 2025). Following the canonical definition proposed by Schwartz et al. (2020) and widely adopted in the computer science literature (Xu et al., 2021), we define Green AI as the ability "to obtain novel results without increasing computational cost, or ideally reducing it." While this perspective is widely viewed as promising, empirical evidence remains scarce on whether AI delivers net environmental gains once the energy used to deploy and operate AI systems is taken into account. In this section, we take a first step toward such a net accounting by (i) bounding the direct electricity consumption of the AI infrastructure used to operate the control system at scale, and (ii) combining these measurements with conservative life-cycle estimates for the broader AI system.

Direct electricity consumption from AI use: metered upper bounds. A key advantage of our setting is that Purecontrol operates its computing infrastructure internally rather than relying exclusively on third-party cloud providers. This allows us to directly measure the electricity use of the AI system using internal server monitoring data. All AI workloads (production, development, and testing) run on a set of virtual machines hosted on a limited number of physical computer servers. Because these services can migrate across servers over time, we adopt a deliberately conservative strategy: we construct an upper bound at the level of physical servers. Using internal monitoring data (Grafana), we (i) map virtual AI services to the physical servers that host them, and (ii) sum conservative server level caps based on one month of observed power consumption. Since the mapping changes over time, this bound is intentionally coarse but safely conservative.

Using computer server monitoring data over a one-month window, we observe server-level peak power draws ranging from roughly 0.3-0.4 kW for the smaller production nodes up to about 1.5 kW for the largest node. Electricity consumption is stable over time. To obtain an upper bound robust to short-lived peaks and measurement noise, we apply a conservative uplift (peak +10%) and an additional safety margin at the node level, and then sum across all nodes used to host AI-related services across environments. This yields a total upper bound of approximately

$$P^{\mathrm{AI}}_{\max} \approx 5.6 \text{ kW}$$

for the entire compute equipment supporting all its customers in the water treatment sector.

Because peak load is an extreme scenario, we also compute a more representative bound using the observed node-level average power draw over the same monitoring window, again applying a conservative margin. This yields an upper bound of about

$$P_{\mathrm{avg}}^{\mathrm{AI}} \approx 4.0 \text{ kW}.$$

Assuming continuous operation, we convert these power bounds into annual electricity use by multiplying by the 8,760 hours in a year. Applying this to the conservative average and peak power estimates yields:

$$E^{\mathrm{AI}} \in [P_{\mathrm{avg}}^{\mathrm{AI}}, P_{\mathrm{max}}^{\mathrm{AI}}] \times 8760 \quad \Rightarrow \quad E^{\mathrm{AI}} \in [35, 49] \text{ MWh/year}.$$

Crucially, this computing infrastructure serves roughly 500 plants, of which about half are Veolia sites. When we distribute the entire electricity use of this computing assembly across plants, the implied order of magnitude is on the order of 70–100 kWh per plant per year. Even if we conservatively attribute the entire electricity use to the Veolia fleet, the implied figure remains below twice this amount. When benchmarked against the operational electricity reductions documented in the previous subsection, the direct electricity used to run the AI infrastructure is well below 1% of the electricity savings generated by AI-driven optimization. We estimate the energy saving of AI in absolute values to be around 2600 kWh/month on average across plants, which corresponds to 31,2 MWh/year per plant on average (see Appendix Table E.4.)

Lifecycle emissions of AI: a conservative accounting framework. Direct electricity is only one component of AI's footprint. A broader accounting must also include upstream emissions associated with deployment and maintenance (e.g., additional on-site hardware, software development, and deployments). Producing a full life-cycle assessment (LCA) that matches standardized protocols is beyond the scope of this paper; however, we can build a transparent and conservative estimate based on a detailed internal assessment of the AI product life cycle.

The internal LCA framework defines the functional unit as the continuous optimization of a site over one year and decomposes impacts into (i) incremental hardware on the client site when required, (ii) software development and platform infrastructure, (iii) deployment (logistics and potential on-site interventions), and (iv) operational use (data collection, storage, model execution, and monitoring). It does not quantify end-of-life impacts and explicitly excludes emissions from office buildings and employee commuting, which are second-order for the present application.

On the hardware side, the incremental equipment required for deployment is highly heterogeneous: in the best case, existing infrastructure can be reused and incremental embodied emissions are close to zero; in the most equipment-intensive cases, the sum of embodied emissions associated with routers, firewalls, gateways, local servers, and additional probes can reach several hundred $kgCO_2e$ (with an upper range around 750 $kgCO_2e$ for the most equipment-heavy configurations, before annualization). To remain conservative, we consider scenarios in which additional on-site hardware and specialized interventions are required.

On the "use" side, the internal assessment provides an order-of-magnitude decomposition of annual digital energy use per site: data collection and storage (tens of kWh/year), daily AI characterization workloads (roughly 100–150 kWh/year), and a real-time control loop (roughly 270–300 kWh/year), for a total of about 400–500 kWh per site-year. Using a French electricity emission factor of 0.08–0.1 $kgCO_2e$/kWh, this corresponds to about 30–40 $kgCO_2e$ per site-year for the operational (electricity) component.

Putting these components together, and excluding raw material extraction and end-of-life stages (while allowing for conservative assumptions on deployment requirements), the resulting estimate of life-cycle emissions in the conservative case scenario when we attribute hardware changes to the AI system is approximately

$$\text{LCA}^{\text{AI}} \approx 250\text{–}400 \text{ kgCO}_2\text{e per plant-year}$$

in the conservative scenario we consider[18]. Based on the results from the previous section of approximately 1 186 kg CO_2 per year-plant (22.8 kg/week Ã 52), we estimate average annual carbon savings of at least 750 kg CO_2 per year-plant, indicating that the net environmental impact of AI adoption remains positive. It is important to emphasize that these energy savings are observed in plants located in France, where the electricity mix is among the least carbon-intensive globally. Consequently, the associated reductions in carbon emissions are likely to be substantially larger in countries with more carbon-intensive electricity systems.

Implications for the net environmental balance. Taken together, the monitoring-based upper bounds on direct electricity use and the conservative LCA scenario suggest that the environmental footprint of the AI system is small relative to the operational savings it generates in our setting. In particular, our metered upper bound implies that the electricity required to operate the AI compute stack represents less than 1% of the electricity saved through process optimization. Moreover, even under conservative life-cycle assumptions, back-of-the-envelope comparisons indicate that net emissions savings remain positive once AI-related emissions are accounted for.

[18]We thank the Purecontrol teams for sharing their internal assessment used to construct this conservative scenario. Discussions with Veolia and Purecontrol indicate that equipment-heavy deployments and repeated on-site interventions were seldom necessary in practice, and that plants were selected *ex ante* to minimize such requirements.

6 Additional Dynamic Margins of AI control

6.1 AI cost-effectiveness and intertemporal reallocation effects

Effects between peak and off-peak hours. To further examine how AI impacts electricity costs, we explore the evolution of the intertemporal elasticity of electricity consumption. We follow a methodology similar to Jessoe and Rapson (2014) and Fabra et al. (2021), by measuring the response of consumption to prices. Unlike their approach, which relied on instrumental variables (IV), our setting does not require such a technique: given the micro industrial context, individual plants have no influence on electricity prices, making endogeneity concerns minimal. We examine how the intertemporal elasticity of electricity changes with AI adoption by analyzing the interaction between price and treatment. However, relative to our concerns, the price signal is noisy, because it is affected by weekly and seasonal shifts, while the intertemporal effects, if any, only occurs at the infra-day level[19]; otherwise said, the structure of electricity pricing exhibits limited intra-day variations but important heterogeneity across days: prices are generally lower on Sundays, and there are substantial seasonal patterns. To focus on intra-day price variation with daily data, we create a binary variable indicating whether the price is high relative to its within-day distribution (above the median), and zero otherwise, as most prices are heavily polarized across days. This variable is consistent with our empirical observation (most plants have only two different prices per day). An additional concern is that AI piloting data is only available at the daily level; we therefore focus on highly treated plants.

We find that reallocation is a critical mechanism driving the pattern of electricity consumption. Activating AI does not lead to a uniform reduction in electricity consumption across hours. Demand remains relatively stable during off-peak hours, whereas demand sharply decreases during peak hours. Figure 6 illustrates the effect of AI piloting share, estimated separately with de Chaisemartin and D'Haultfoeuille (2024) for peak and off-peak hours[20]. We find the overall reduction in electricity consumption to be entirely driven by a substantial decrease during peak hours. Average weekly electricity consumption during peak hours declines by 7.4%, whereas consumption during off-peak hours remains essentially unchanged (-1.7%, n.s.), resulting in an average reduction of 5.4% when considering all hours combined. In complement, in a TWFE specification, in Appendix Figure K.3, we find that the effect is substantial enough for the price elasticity to reverse: while electricity consumption was 7 percentage points higher during peak hours before AI adoption, it becomes 3 percentage points lower during off-peak hours after AI implementation. These findings show that the AI in industry indeed permit to reallocate electricity demand from

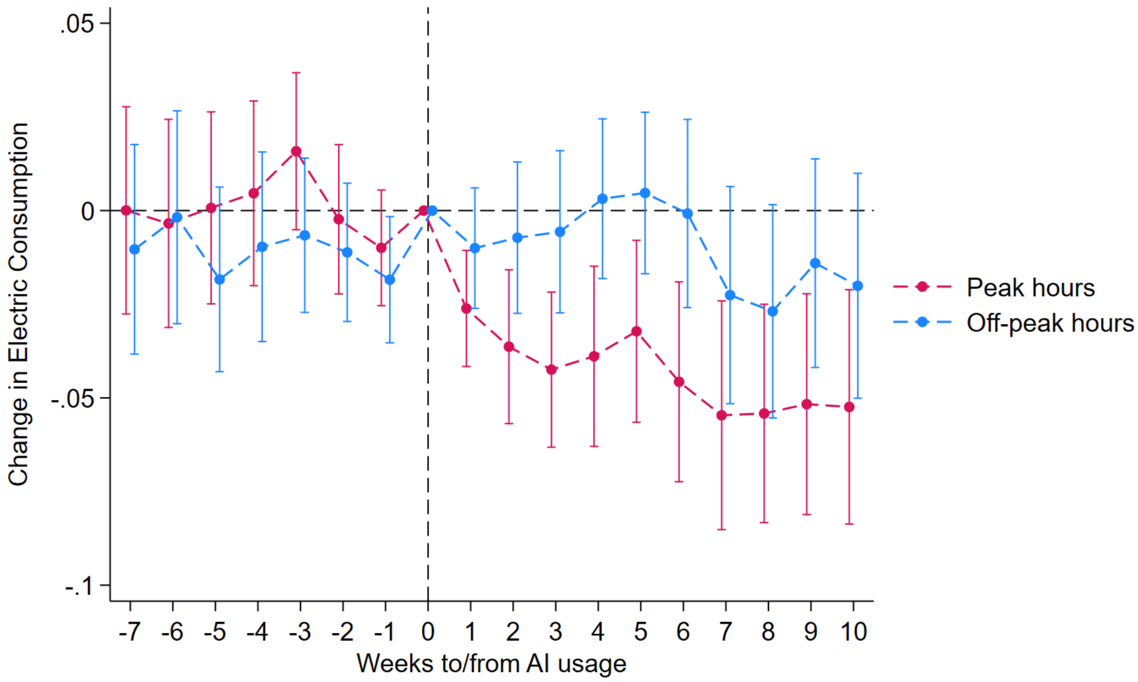
[19]Maintaining safety margins and operational constraints typically restrict the ability of plants to shift consumption across days. The reallocation might only occur across a couple of hours

[20]The division between peak and off-peak hours is generally consistent across days and seasons for a given plant, which justifies the relevance of this specification.

peak toward off-peak hours, consistently with previous findings on households energy demand (Metcalfe et al., 2026).

Figure 6: Power savings between peak and off-peak hours

(a) Event study



(b) Average cumulative total effect per plant

	Estimate	Std. Error	95% CI Lower	95% CI Upper
All hours	-0.054***	0.017	-0.087	-0.021
Off-peak hours	-0.017	0.017	-0.051	0.016
Peak hours	-0.074***	0.017	-0.108	-0.04

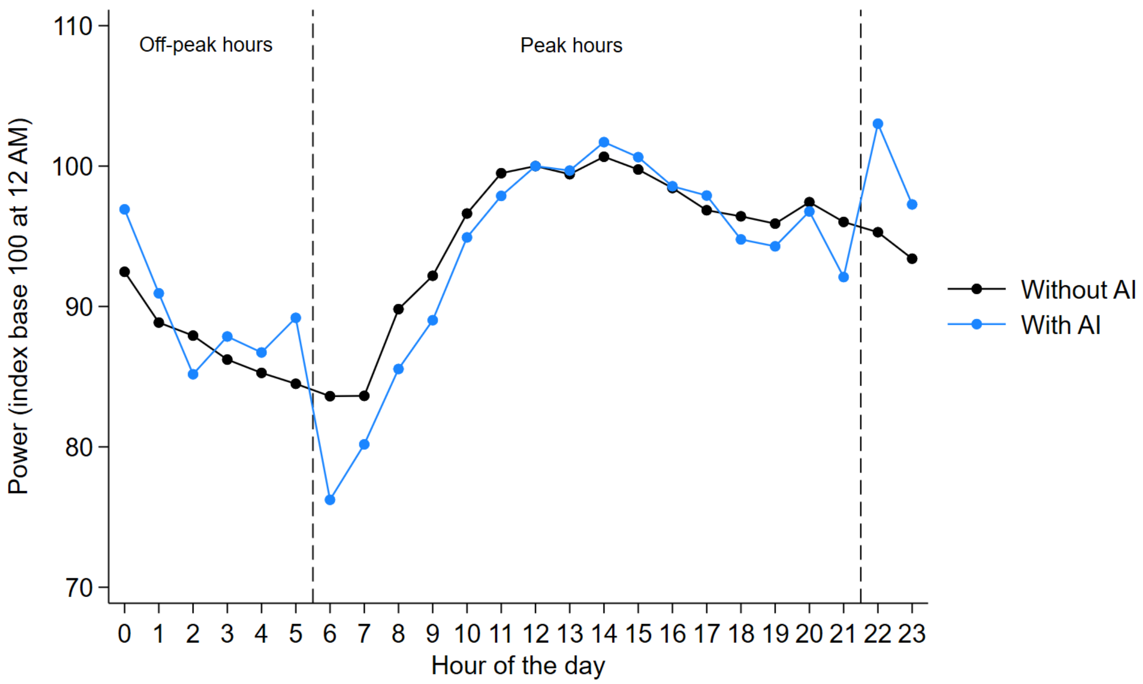
Notes. This figure plots the coefficients and 95% confidence intervals from the event-study regression using de Chaisemartin and D'Haultfoeuille (2024). Subfigure (a) separates the sample between off-peak and peak hours and aggregates outcomes at the weekly level. Subfigure (b) reports the average cumulative total effect measured over 10 weeks. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To further validate our findings and explore the mechanisms driving these shifts, we compare the relative electricity consumption patterns across different hours of the day. In Figure 7, we compare hourly consumption profiles when controlled and not controlled by AI[21]. While this analysis is descriptive in nature, it provides valuable insights into how electricity consumption evolves throughout the day. Our results clearly show that the

[21] We compute a weighted average using weights equal to the inverse of the number of observations per id and hour, so that each id contributes equally to the hourly mean.

differentiated electricity consumption patterns during peak and off-peak hours are driven by a reallocation mechanism. Notably, the reduction in consumption across these periods is not uniform: we observe two clear kink points at the beginning and end of the peak hours. At the onset of the peak period, there is a sharp 20% reduction in electricity consumption, followed by a 10% increase towards the end of the peak period. Furthermore, we find that electricity consumption during the beginning and end of the peak period is lower in AI-managed plants compared to the counterfactual without AI, while the reverse holds true for the off-peak period. These pronounced discontinuities at the start and end of the peak period suggest that the price signal effectively drives behavior, allowing the system to anticipate and shift consumption ahead of the peak and defer it to the end within a few hours of the threshold. On the contrary, during the middle of the peak period (from 12 p.m. to 5 p.m.), consumption remains largely unaffected by the reallocation, indicating that the mechanism operates primarily around the edges of the peak window.

Figure 7: Daily relative consumption profiles with and without AI



Notes. This figure compares the weighted average of the electricity consumption profiles where each plant receive an equal weight per hour, between treated days ("With AI") and non-treated days ("Without AI"). We focus on relative consumption levels: for each group, consumption is normalized to 100 at 12 a.m. The figure also highlights peak and off-peak hours, which are common across plants and do not vary over the year.

In theory this pattern is likely to generate both reduction in electricity costs and in environmental footprint, because the carbon intensity of electricity demand in generally stronger in peak periods. However, as we show in Appendix Figure K.1, the peak / off-peak shift is not discriminative enough: in our sample, the average carbon intensity during peak hours is only about 5% higher than during off-peak hours. It explains why we cannot, counterintuitively, detect a stronger effect of AI use on carbon footprint than on electricity consumption in Table 3, despite the reallocation effect. This result advocates for a reinforcement of the price signal sensitivity through a more comprehensive consideration of supply-side heterogeneity and a shift towards more dynamic, real-time pricing schemes for industrial electricity consumers. Indeed, a more dynamic pricing system, reflecting intra-day variability in carbon intensity (that we see in Appendix Figure K.2) and electricity demand, could amplify AI's benefits and encourage industries to further optimize their energy usage patterns in alignment with both environmental goals and economic incentives. Hence, although price reallocation is not a direct lever for reducing carbon footprints in this context, it could become a significant factor in a grid for which the carbon intensity of electricity supply varies across hours, coupled with a pricing scheme that reflects this variability. It highlights the potential of AI not only as an operational tool for energy efficiency but also as a mechanism for driving policy changes in electricity pricing.

6.2 AI in Periods of Weather Stress

Extreme precipitation is a first-order operational stressor for wastewater treatment plants (WWTPs) in our setting: rainfall episodes are strongly correlated with short-run movements in electricity use, consistent with the idea that inflow surges and hydraulic constraints mechanically translate into higher pumping and process demand. This motivates the hypothesis that the value of AI-based control is concentrated in extreme-weather episodes, when conventional operations face binding constraints and electricity use tends to spike.

Empirical specification and precipitation definitions. To study whether AI attenuates the operational and energy consequences of extreme precipitation, we estimate:

$$\log(Y_{i,d} + 1) \;=\; \beta D_{i,d} + \gamma R_{i,d} + \delta\,(D_{i,d} \times R_{i,d}) + \mu_i + \lambda_d + \varepsilon_{i,d}, \tag{4}$$

where $Y_{i,d}$ denotes electricity consumption of plant i on day d, $D_{i,d}$ captures AI operation (we consider alternative measures, including a binary treatment indicator, a higher-intensity treatment definition, and a continuous "pilotage share" measure), and μ_i and λ_d are plant and day fixed effects. Because the dependent variable is in logs, γ and δ can be interpreted as semi-elasticities.

We operationalize "extreme precipitation" using two complementary indicators. The first one captures hourly precipitation volume:

$$R_{i,h}^{\text{hourly}} = \mathbb{1}\{\text{Rain}_{i,h} > \tau\},$$

where $\text{Rain}_{i,h}$ is hourly rainfall. The second one captures the overall effect of rainfall episode at the day-level:

$$R_{i,d}^{\max} = \mathbb{1}\left\{\max_h(\text{Rain}_{i,h}) > \tau\right\}.$$

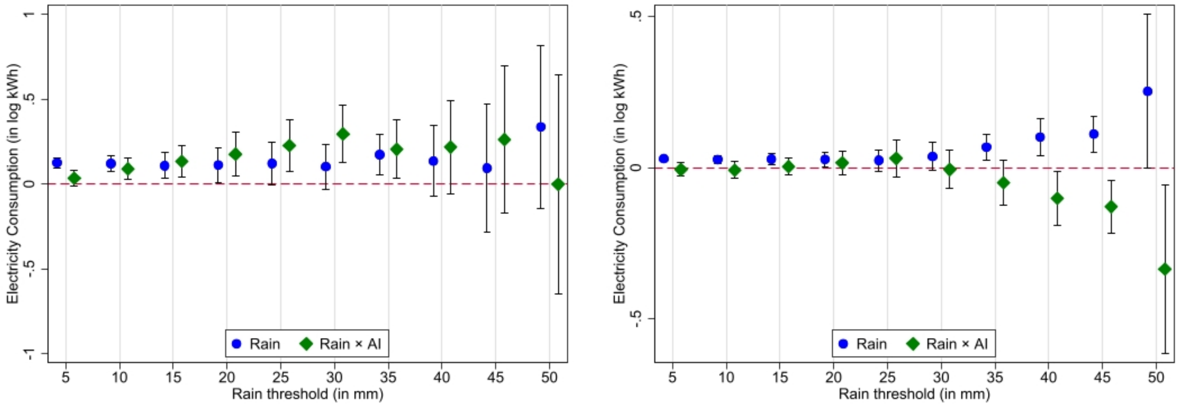
We sweep the threshold τ over a range of high cutoffs in the right tail of the empirical distribution, plotted in the Appendix Section D.8.

The role of precipitation intensity and concentration. Using the hourly precipitation measure $R_{i,h}^{\text{hourly}}$, Panel (a) Figure 8 logically shows that exceedances of high rainfall thresholds are associated with sizeable contemporaneous increases in WWTP electricity consumption (a positive γ). More importantly to our topic, we estimate a positive interaction with AI operation (a positive δ), and the magnitude of this interaction varies systematically with shock intensity: the incremental response under AI is negligible at low thresholds, becomes statistically significant at the 10 mm threshold, and rises gradually up to 30 mm. This pattern suggests that AI leads plants to react more sharply and more proportionally at the time the shock arrives. In other words, during the hours in which extreme rainfall occurs, AI does not reduce electricity use; instead, it reallocates effort toward real-time adjustment, increasing consumption in a targeted manner when inflows spike.

Panel (b) of Figure 8 examines the same episodes at the daily level using $R_{i,d}^{\max}$. Up to 30 mm, we detect little effect on daily consumption. Starting around 35 mm, however, rain shocks generate markedly larger increases in daily electricity demand under conventional (non-AI) operation, consistent with acute inflow surges and binding capacity constraints. For these high-intensity events, the rain-induced increase is of similar order of magnitude at the hourly and daily horizons, indicating limited scope for intertemporal smoothing under rule-based automation[22]. Crucially, these are precisely the episodes for which AI delivers its largest mitigation effects. The interaction term δ is of comparable magnitude and opposite sign to γ, implying that the incremental daily electricity consumption associated with extreme rainfall is largely offset under AI operation. Across thresholds, the evidence is consistent with near-complete compensation: while extreme precipitation mechanically raises electricity demand under conventional control, AI brings daily consumption back toward the counterfactual level observed on non-extreme days.

[22]This finding is consistent with our assumption that, absent AI, plants adjust sluggishly to sudden inflow surges.

Figure 8: Intense rainy episodes and their attenuation through AI use.



Thr.	5	10	15	20	25	30	35	40	45	50
IPW	10^2	10^3	10^3	10^4	10^4	10^4	10^4	10^5	10^5	10^5

(a) At the hour-level

Thr.	5	10	15	20	25	30	35	40	45	50
IPW	10^1	10^2	10^2	10^2	10^3	10^3	10^3	10^3	10^3	10^4

(b) At the day-level

Notes. Panel (a) reports estimated effects using the hourly precipitation measure $R_{i,h}^{\text{hourly}}$. The first series corresponds to the effect of exceeding the rainfall threshold τ, while the second series reports the interaction between threshold exceedance and AI use (scaled by the AI-use intensity). Error bars display 5% confidence intervals. Panel (b) reports the corresponding estimates at the daily level using the maximum daily precipitation measure $R_{i,d}^{\max}$. Markers and confidence intervals are defined as in panel (a). The table below the panels reports the inverse probability weights (IPW), i.e., the inverse of the frequency at which an observation in the sample exceeds each rainfall threshold.

The attenuation therefore does not appear to operate by suppressing consumption at the peak hour of the incident. Instead, the mitigation shows up when aggregating over the day. This pattern is consistent with AI acting as a supervisory control that reallocates effort intertemporally: it may respond aggressively (and energy-intensively) at the time of the shock to maintain process stability or compliance, but then prevents a prolonged elevation in electricity use over subsequent hours, delivering almost-normalized daily totals. Appendix Figure L.1 corroborates this interpretation: while both curves surge sharply at rain onset (t = 0), the AI-equipped plants reach far more rapidly a higher instantaneous peak, yet their index also falls back below baseline faster thereafter. Non-AI plants, by contrast, sustain a persistently elevated plateau throughout the post-event window. In other words, the main benefit of AI in extreme precipitation episodes appears to be improved within-day management of the operational shock, smoothing the daily electricity profile rather than reducing instantaneous consumption at the moment of maximum stress.

Appendix Figure L.2 repeats the analysis using total daily precipitation, a daily analogue of $R_{i,h}^{\text{hourly}}$. The qualitative pattern is similar but estimates are less precise, with statistically significant effects only for very large daily totals (above 80 mm/day). Taken together, these results point to concentration as a key state variable: AI appears particularly effective at mitigating highly concentrated rainfall episodes, precisely the situations in which simple threshold-based automation is least suited to regulate the process.

Other meteorological conditions. We further examine whether AI adoption differentially moderates the effect of other meteorological conditions on electricity consumption. Using the same empirical strategy, we test for extreme low minimum temperatures, high maximum temperatures, extreme humidity, and water pressure. Across all specifications, we find no statistically significant interaction effects. Although these meteorological variables are correlated with electricity consumption at the plant level, the magnitude of these relationships is substantially smaller than for intense rainfall episodes. As a result, any moderating effect of AI, if present, is likely too limited for the interaction terms to be estimated with sufficient statistical power.

6.3 AI and the management of effluent quality

Effluent Average Quality. We verify that AI monitoring and the reduction of electricity consumption do not come at the expense of effluent quality, especially in the removal of nitrogen compounds in treated water. We investigate how AI impacts the nitrification process, whose goal is to remove ammonium (NH_4^+) and convert it into nitrates (NO_3^-) through aeration of the effluent, and the denitrification process, whose goal is to remove nitrates and convert them into gaseous nitrogen (N_2), which then naturally escapes from the water to the atmosphere[23]. We also examine the effect on phosphate (PO_4^{3-}) concentrations. Unlike nitrogen removal, phosphate elimination is less dependent on aeration[24]. We rely on manual sampling of treated water for these pollutants. Appendix Table J.1 reports TWFE estimates using plant and date fixed effects. The results show that AI significantly reduces nitrate concentrations by 0.51 mg/L and ammonium concentrations by 0.29 mg/L, relative to baseline levels of 1.97 mg/L and 1.73 mg/L respectively. By contrast, we find no significant effect on phosphate concentrations, which suggests that AI-driven aeration management does not interfere with the phosphate elimination process.

Compliance with pollution regulatory standards. Wastewater treatment plants are subject to pollutant discharge limits that vary across plants and over time due to local regulations. Using data on compliance with ammonium and phosphate thresholds, we estimate the effect of AI adoption on the likelihood of meeting these standards. Appendix Table J.2 reports the results from conditional logistic regression models including plant fixed effects. AI usage has a positive and statistically significant effect on ammonium compliance. The estimated coefficient implies that, within a given plant, AI usage increases the odds of meeting ammonium discharge limits by about 79%. We find no statistically significant effect of AI usage on phosphate compliance, consistent with our previous findings on phosphate concentrations.

[23] We provide a further description of the nitrogen removal process in Appendix Sections J.1 and J.2.

[24] It is mainly achieved through phosphorus uptake by polyphosphate-accumulating organisms (PAOs) and through chemical precipitation. But poor aeration management can nonetheless impair its removal (Deronzier and Choubert, 2004)

The triple dividend of AI. We then focus on the heterogeneity of these results depending on the ammonium concentration. The marginal benefits of AI are concentrated in periods of high ammonium load, precisely when the biological process is the most stressed and conventional rule-based aeration performs poorly. When influent ammonium is elevated, oxygen demand rises sharply; standard control logic typically responds by increasing aeration, which both (i) drives up electricity consumption and (ii) erodes the anoxic (i.e. oxygen-free) conditions required for denitrification[25]. By contrast, AI delivers a "triple dividend" in these high-load states, as we illustrate in Figure 9, by dynamically maintaining an appropriate oxygenation balance[26] as a function of basin conditions and by anticipating load spikes. First, AI avoids over-aeration, shifting redox conditions toward denitrification: we observe a decline in oxidation-reduction potential at high ammonium deciles, which coincides with progressively larger reductions in effluent nitrate concentrations, while effects are negligible in the lowest deciles. Second, the reduced reliance on aeration translates into sizable electricity savings, concentrated in the upper six ammonium deciles. Third, despite lower aeration intensity on average, AI improves nitrification performance where it matters most: quantile regressions reported in Appendix Table J.3 show that AI adoption sharply reduces ammonium concentrations in the top decile, consistent with AI primarily mitigating over-limit episodes, while effects on lower quantiles are small and reflect a leftward shift of the overall distribution.

7 Welfare and Climate Significance

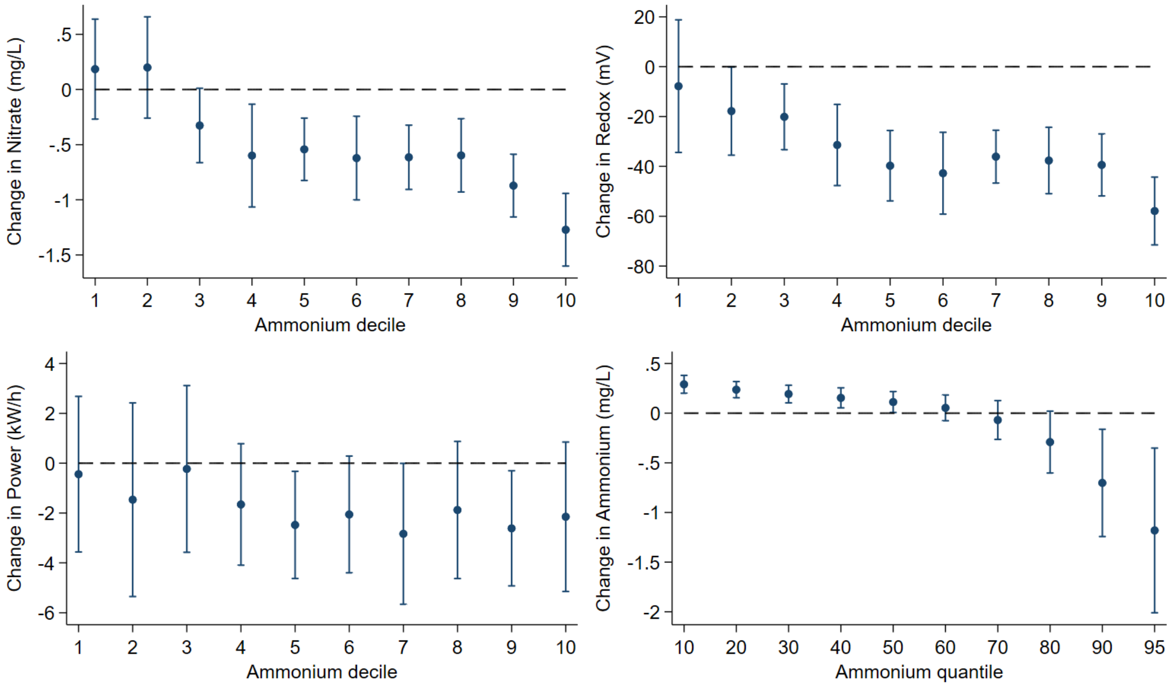
In order to gauge the potential importance of our findings for global climate and welfare, we integrate AI-induced energy efficiency improvements in the DICE climate-economic model (Barrage and Nordhaus (2024)). We consider three scenarios which respectively apply our estimated treatment effects to: (1) global wastewater treatment electricity consumption ("WWTP only"), (2) wastewater treatment plus energy demand from industrial drying and steel galvanization - two other processes for which Purecontrol has already developed similar solutions - ("WWTP+"), and (3) all energy use ("All"). Extrapolating beyond wastewater treatment is motivated by the fact that there are many industrial *endpoint control* processes where an unobservable target must be met and where digital twins could help improve energy efficiency over fixed-time application or rules of thumb (e.g., industrial drying, cooling, fermentation, metallurgical processes like galvanization).

We formally incorporate both the emissions reduction and energy saving benefits of AI in the model as follows. First, we introduce a permanent level shift in the baseline energy-

[25] In activated-sludge systems, excessive aeration raises dissolved oxygen in the basin; since heterotrophs preferentially use oxygen as an electron acceptor, denitrification is inhibited, leading to higher effluent nitrate.

[26] Also known as an anoxic/aerobic balance. We use "aerobic" to denote oxygenated conditions (necessary to the nitrification process to take place) and "anoxic" to denote low-oxygen conditions (necessary to the denitrification process to take place).

Figure 9: Effect of AI and ammonium concentration heterogeneity



Notes. The first three panels present TWFE estimates of the marginal effect of AI usage on nitrate (NO_3^-) concentrations (mg/L), redox potential (mV), and electricity consumption (kWh) across deciles of the NH_4^+ distribution, controlling for plants and date fixed effect, with standard errors clustered at the plant level. Results tables are in appendix J.4. The bottom-right figure shows quantile regression with plant fixed effects estimates of the effect of AI usage on NH_4^+ concentrations across the conditional distribution from the 10th to the 95th quantile. The result table for the quantile regression is in Appendix J.3. Confidence intervals are bootstrapped with standard errors clustered at the plant level.

based CO_2 intensity of production in the DICE-2023 model (base scenario) of -6% applied to the relevant emissions shares, which are (1) 0.4% of emissions for "WWTP only",[27] (2) 5% of emissions for "WWTP+",[28] and (3) 100% of energy-related emissions for "All." This first step is used to calculate the climate benefits of the new technology. Second, we model energy savings through a permanent level increase in total factor productivity (TFP) proportional to an assumed aggregate energy expenditure share of 4% (Golosov et al. 2014) and the relevant emissions share of each scenario.[29] For example, in the "WWTP+" scenario, we increase TFP by 4%*5%*6% = 0.012%. This second step is

[27]We combine IEA (2016*b*)'s estimate that WWTP account for 1% of global electricity consumption with the global average CO_2 intensity of electricity (0.0005 GtCO2/TWh, calculated from IEA (2025*b*) and IEA (2016*a*)) and divide by total CO_2 emissions from all energy combustion (IEA (2016*a*)) to arrive at 0.4%.

[28]Drying is frequently estimated to account for 10-25% of industrial energy demand (e.g., da Silva et al. (2025); Bayati et al. (2025); Mujumdar (2007)). Combining a central value of 15% with a 30% estimated share of total energy demand from industry (IEA (2024)) yields an energy emissions share of 4.5% for drying. For galvanization, we combine a CO_2 intensity of 0.2 kg CO_2 per kg of steel from Álvarez-Álvarez et al. (2025) with a lower bound on global galvanized steel production from WSA (2025) to arrive at an estimated global emissions share of 0.1%.

[29]For simplicity, this calculation takes emissions shares as a proxy for energy expenditures shares.

necessary as DICE does not model energy as an explicit input to production.

Table 4 summarizes the results. The estimated global welfare gains associated with our estimate of AI-induced energy efficiency improvements reductions are (1) $149 billion ($2025 PPP) in the "WWTP only" scenario, (2) $1.8 trillion in the "WWTP+" scenario, and (3) $36 trillion in the "All" scenario. Around half of the welfare increase is due to avoided climate damages and energy savings, respectively. While these calculations are highly optimistic in assuming a fast global roll-out of the technologies we study, they provide an order-of-magnitude sense that the global stakes from AI-induced energy efficiency improvements are large.

Table 4: Global Welfare Gains ($2025 PPP) from AI Energy Efficiency Improvements

Processes Covered	% Energy CO_2 Emissions	Welfare Gain Climate	Welfare Gain Climate & Energy Savings
WWTP	0.4%	$75 bil.	$149 bil.
WWTP+	5%	$940 bil.	$1.8 tril.
All	100%	$18.8 tril.	$36 tril.

8 Conclusion

This paper studies whether industrial AI can deliver net environmental benefits once its own footprint is accounted for. Using high-frequency operational data from a large fleet of wastewater treatment plants and quasi-experimental variation from staggered adoption and non-absorbing exposure to AI control, we estimate the causal impact of an AI-driven digital twin on electricity consumption and CO_2 emissions. We find economically meaningful reductions in both outcomes: 5.4% and 6% in the first ten weeks of AI operation for electricity consumption and carbon footprint respectively, and 8.2% for electricity costs. Overall, our findings provide micro-level evidence consistent with the view that AI-enabled process optimization can generate substantial emissions reductions in industry (IEA, 2025*a*). These savings also imply strongly negative abatement costs, on the order of –€6,300 per ton of CO_2, meaning that the technology pays for itself while reducing emissions.

AI enhances process efficiency in aeration, one of the most energy-intensive stages of wastewater treatment, by leveraging a richer real-time information set than rule-based control and by dynamically adjusting operating setpoints. The evidence points to several distinct channels through which AI improves energy efficiency. First, a large share of the gains stems from responding to short-run heterogeneity in inflows: AI reduces hours of over-aeration and scales back activity when inflow levels are low. Second, AI limits the electricity surges triggered by extreme and concentrated rainfall events, adjusting more flexibly to abrupt inflow spikes than conventional automation rules allow. Third, AI improves the management of chemical pollution peaks. When influent ammonium load is elevated, conventional rule-based aeration tends to over-aerate, simultaneously driving up electricity consumption and eroding the anoxic conditions required for denitrification. AI avoids this trade-off by dynamically maintaining the aerobic/anoxic balance and anticipating load spikes, delivering simultaneous gains in energy efficiency and effluent quality precisely when the biological process is most stressed. Taken together, these three channels suggest that AI-based control is particularly valuable under operational stress, when the limitations of fixed automation rules are the most binding. In addition, AI reshapes the intraday profile of electricity use. Reductions are concentrated during peak hours, which helps explain why electricity costs fall by more than consumption and carbon emissions. Under efficient grid pricing, this load-shifting capacity could constitute an additional lever for carbon emissions reduction.

Beyond the mechanisms at play, a central contribution of the paper is to move beyond indirect proxies and provide a net accounting of Green AI's environmental implications in an industrial setting. Using provider-side metering data and conservative life-cycle assumptions, we bound the electricity use and associated emissions attributable to operating the AI system, and compare them to the operational savings achieved at plants. The AI system's own electricity consumption is small relative to the downstream reductions it induces, implying positive net emissions savings even under conservative assumptions. While our estimates pertain to a particular AI tool deployed in a single industry, the mechanism – machine-learning-enabled control that improves the efficiency of energy-intensive operations – is likely to be relevant in other process industries. Consistent with this interpretation, the technology provider reports deploying closely related digital-twin systems beyond wastewater aeration, including steel galvanization in metallurgy, anaerobic digestion for biogas production, water-network operations, and agri-food processes. Given the breadth of processes where similar endpoint-control logic could apply, we complement our micro-level estimates with a macroeconomic assessment. Integrating our treatment effects into the DICE climate-economic model, we find welfare gains of $1.8 trillion from avoided CO_2 emissions when extrapolating to processes where comparable solutions are already proved to be technically feasible, rising to $36 trillion under full energy-use extrapolation. These figures illustrate the potential aggregate significance of AI-enabled efficiency gains, though the broader scenarios require extrapolation and should be interpreted accordingly. Extending the analysis to additional sectors, operating environments, and electricity systems would help assess external validity and quantify heterogeneity in impacts.

Yet, this potential will not materialize spontaneously. The pace of AI adoption to automate workflows and data analysis remains slow. Previous evidence showed that technologies with low or negative abatement costs can remain under-deployed due to informational and organizational barriers (Gerarden, Newell and Stavins, 2017). Should this pace of diffusion remain too modest, the identified benefits may only be partially realized. The diffusion of specialized AI applications is therefore a matter of economic policy and organizational change.

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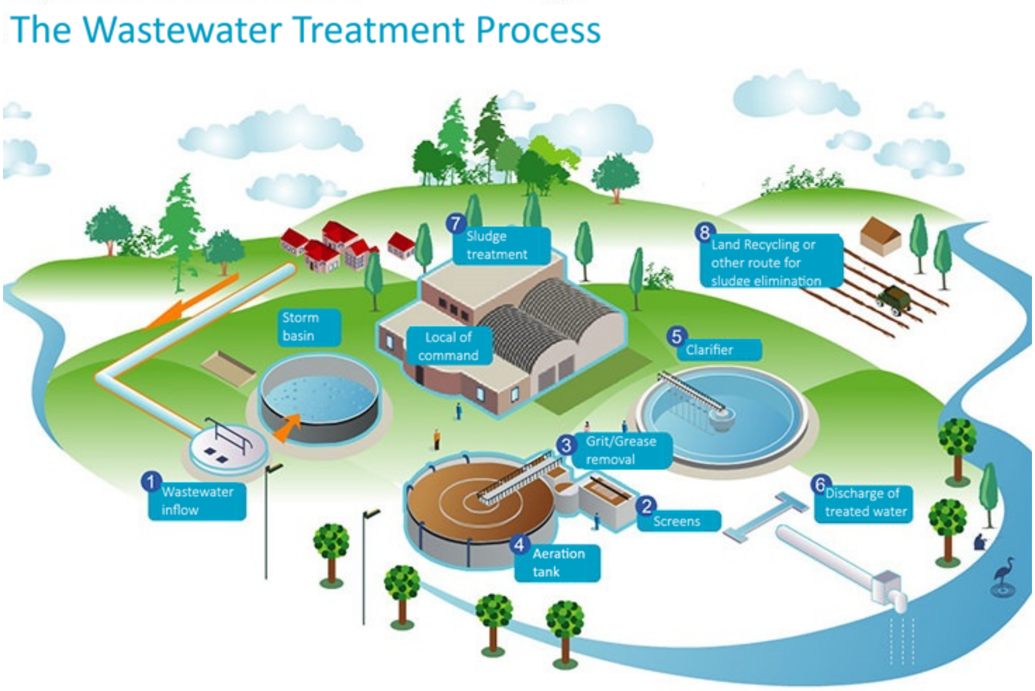
Appendix

A Wastewater Treatment Plant Diagram and Photo

Figure A.1: Diagram of a typical activated sludge WWTP



Notes. This diagram is adapted from a presentation of SDEA (2017).

Figure A.2: Aerial Photo of the WWTP of Bonneville (activated sludge)

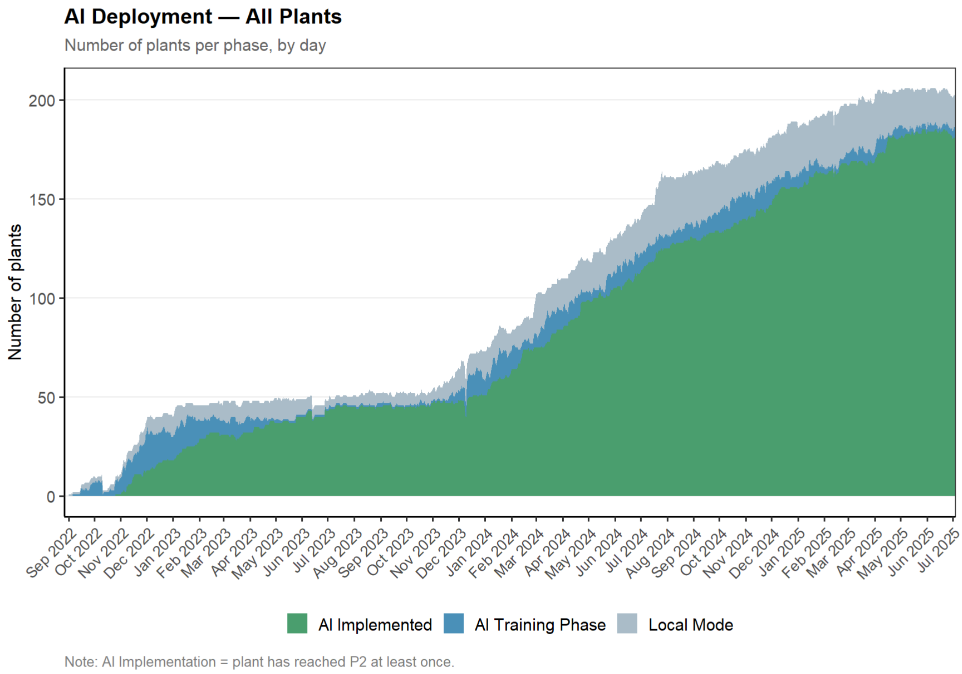
Notes. This photo was provided by Veolia.

B AI deployment

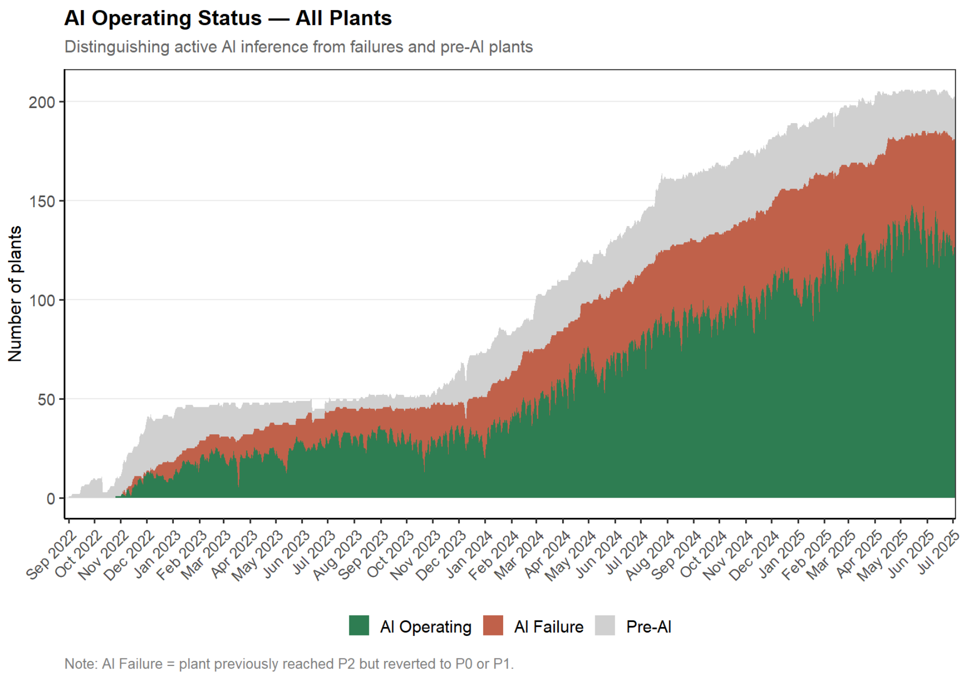
Figure B.1: Evolution of control modes of a typical plant

Notes. This figure presents the temporal evolution of control modes governing the plant's aeration system. The three modes are distinguished: P0 (local control operated directly by plant management), P1 (manual supervision by Purecontrol), and P2 (AI-driven automated control). The AI-authorization indicator denotes the plant management's authorization for Purecontrol to manage the aeration process, whether under manual (P1) or AI-optimized (P2) control.

Figure B.2: Roll-out of AI adoption and use.



(a) Plant with AI installed



(b) Plant with operating AI

Note: In subfigure (a), we are interested to the phase of AI implementation (not implemented, in training or installed). In subfigure (b), we are interested in AI operating status (not yet installed, operative or failing).

C Digital Twins

Figure C.1: Generic Diagram of a Digital Twin

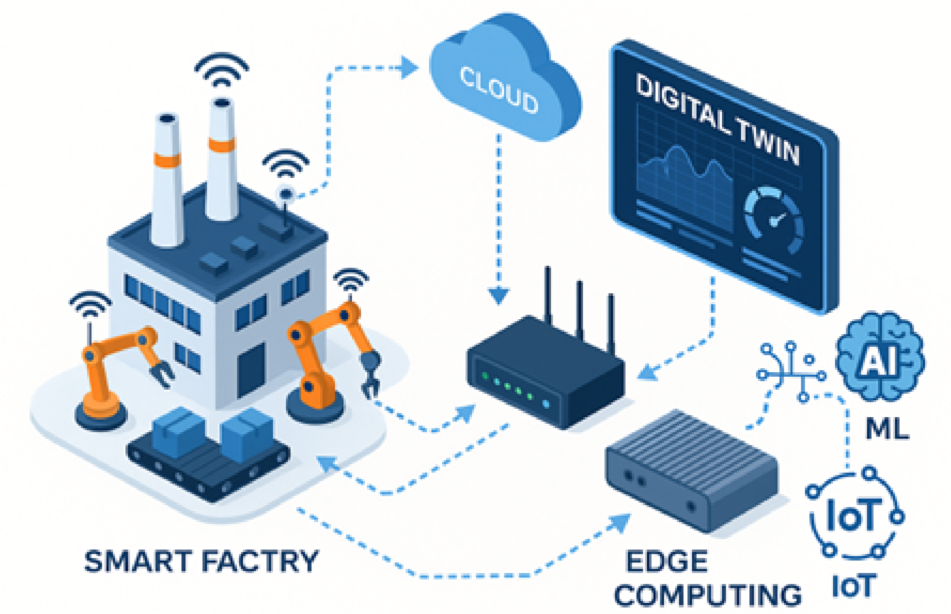
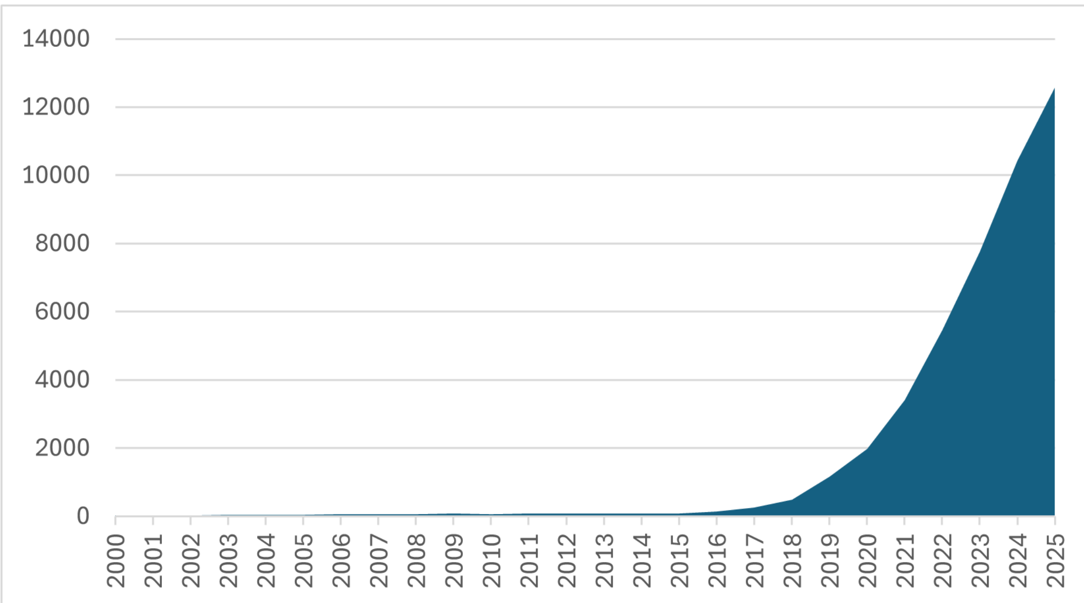


Figure C.2: Occurrence of “Digital Twins” in Research

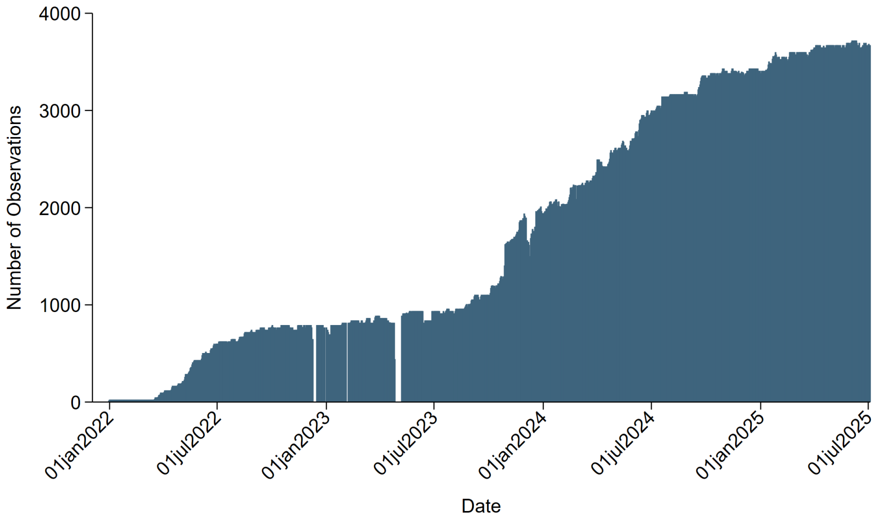


Notes. This figure plots the occurrence of “Digital Twins” (article title, abstract, keywords) by year in the Scopus database.

D Additional Descriptive Statistics

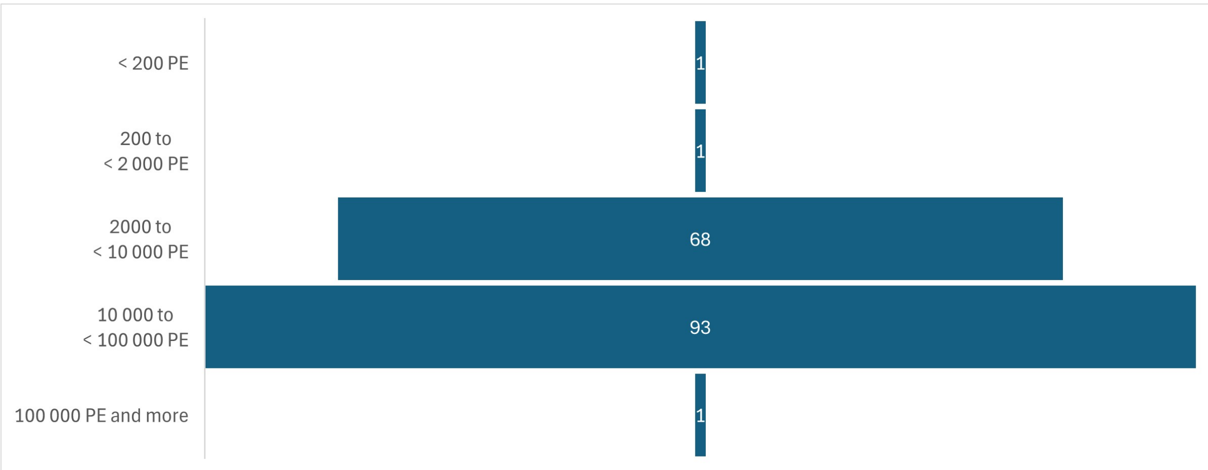
D.1 Number of observations by date

Figure D.1: Distribution of observations over the sample



D.2 Comparison of the sample to the French national distribution of WWTP

Figure D.2: Distribution of the number of plants per size in our sample



Notes. This graph shows the number of plant per size category in our sample.

Figure D.3: Distribution of plant nominal capacity

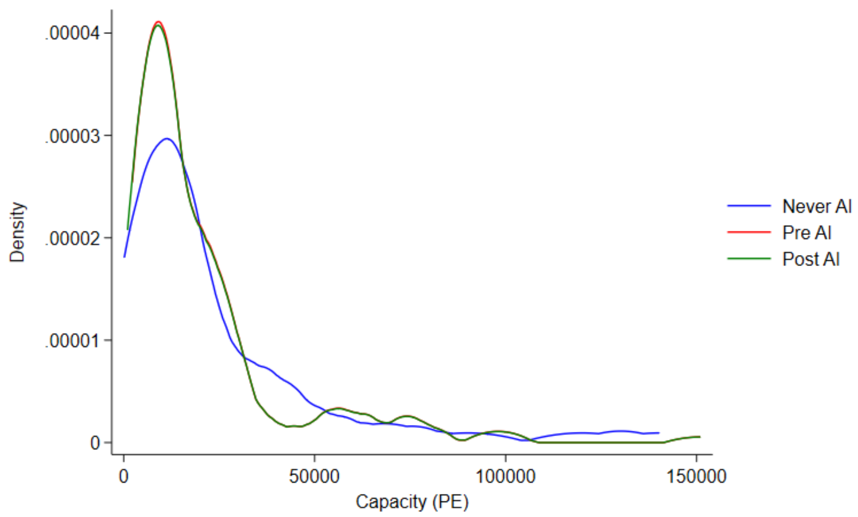


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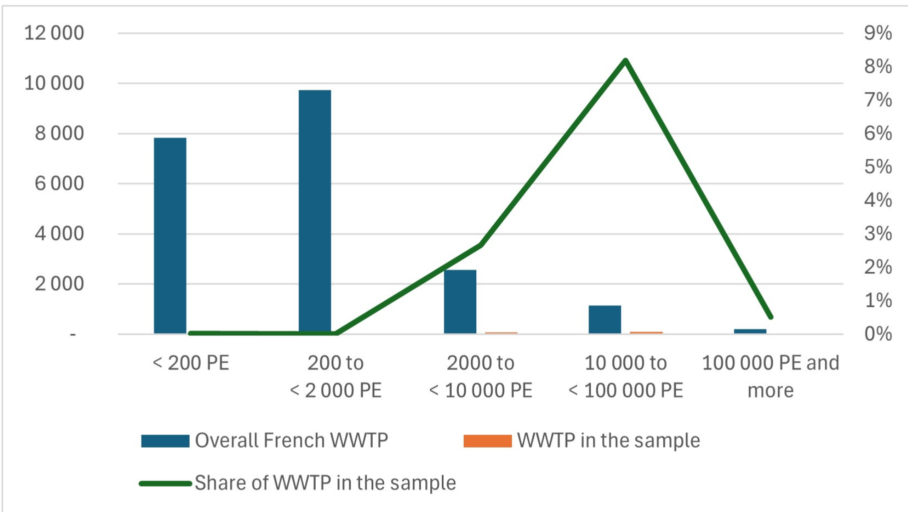
Figure D.4: Distribution of observations over the sample



Notes. This graph shows the absolute number of plants in our sample vs. the French national distribution (Source: CGDD (2019)).

D.3 Statistics by AI adoption wave

Table D.1: Summary statistics by AI adoption waves

Variable	First wave		Second wave	
	(Pre AI)	(Post AI)	(Pre AI)	(Post AI)
Plants	40	-	99	-
Mean adoption date	24 Feb. 2023	-	25 Jul. 2024	-
Nominal capacity (PE)	14,809	-	22,301	-
Observations	188,292	719,060	395,979	785,188
AI usage (Share of time)	0	0.585	0	0.579
Power (kW)	59	56	68	75
Carbon em. ($kgCO_2e/h$)	3.2	1.5	1.8	1.7
Electricity cost (€/h)	3.5	5.4	7.4	9.1

Notes: This table presents the summary statistics of the sample by AI adoption wave, before and after the AI implementation.

D.4 Sample with additional variables

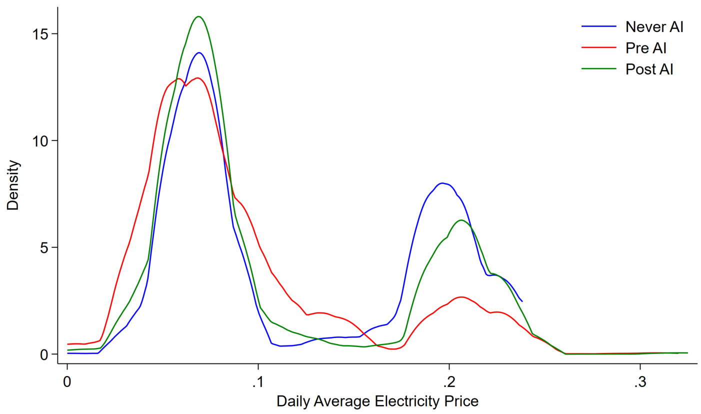
Table D.2: Summary statistics - sample with additional variables

Variable	All	Never AI	Pre-AI	Post-AI
Observations	1,635,615	108,329	264,388	1,262,898
Plants	150	21	90	129
Nominal capacity (PE)	19,199	17,992	21,316	19,396
AI usage (Share of time)	0.45	0	0	0.6
Power (kW)	66.6	85.8	68.6	64.1
Carbon em. ($kgCO_2e/h$)	1.58	2.1	1.7	1.51
Electricity price (€/kWh)	0.12	0.13	0.11	0.12
Electricity cost (€/h)	7.7	11.6	7.7	7.27
Inflow (m3)	115	164	129	109
Rain (mm)	0.13	0.11	0.15	0.13
Redox (mV)	22.17	16.5	30	21

Notes: This table presents the summary statistics of the subsample restricted to 150 plants for which the control variables (inflow, rainfall and redox) are available. The first column consists of all plants in our sample, the second column includes plants who never receive coverage by AI. The third column presents statistics for treated plants before they receive AI installation, and the fourth column includes treated plants after the AI deployment.

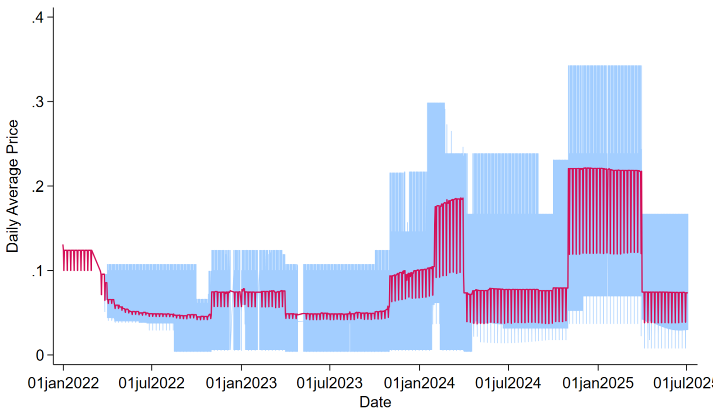
D.5 Electricity price

Figure D.5: Daily electricity price distribution



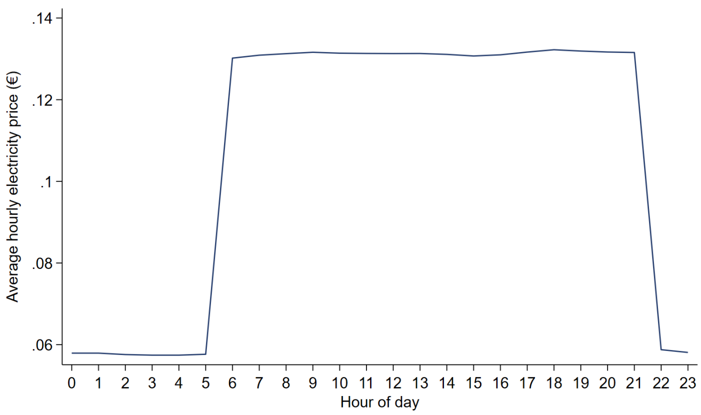
Notes. This graph shows the distribution of the average daily electricity price.

Figure D.6: Daily electricity price trajectories across plants



Notes. The average daily electricity price across plants is plotted in red, while the daily electricity prices of each plants appear in blue.

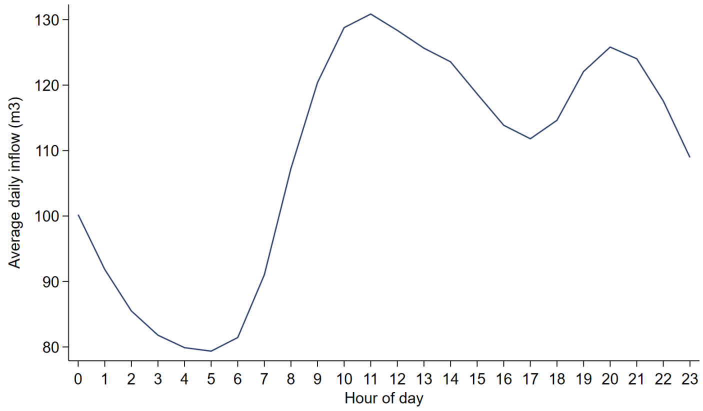
Figure D.7: Daily average electricity price



Notes.

D.6 Inflow

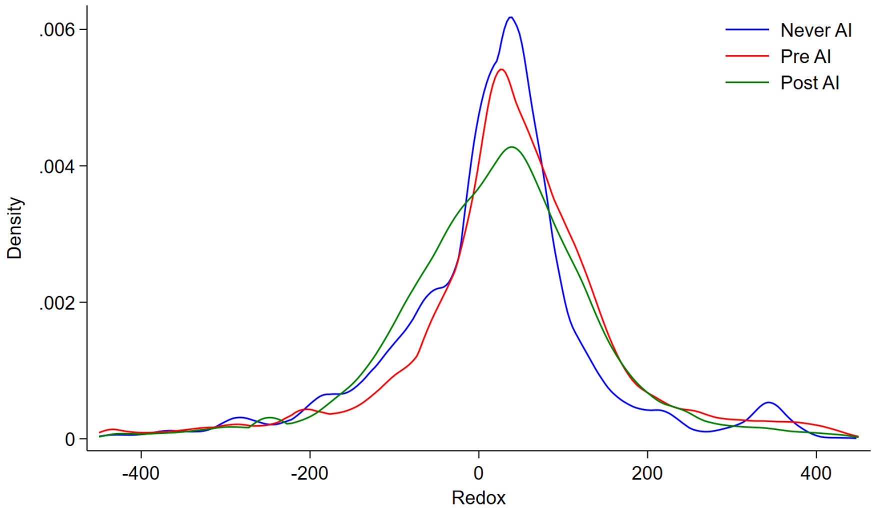
Figure D.8: Inflow during the day



Notes.

D.7 ORP Distribution

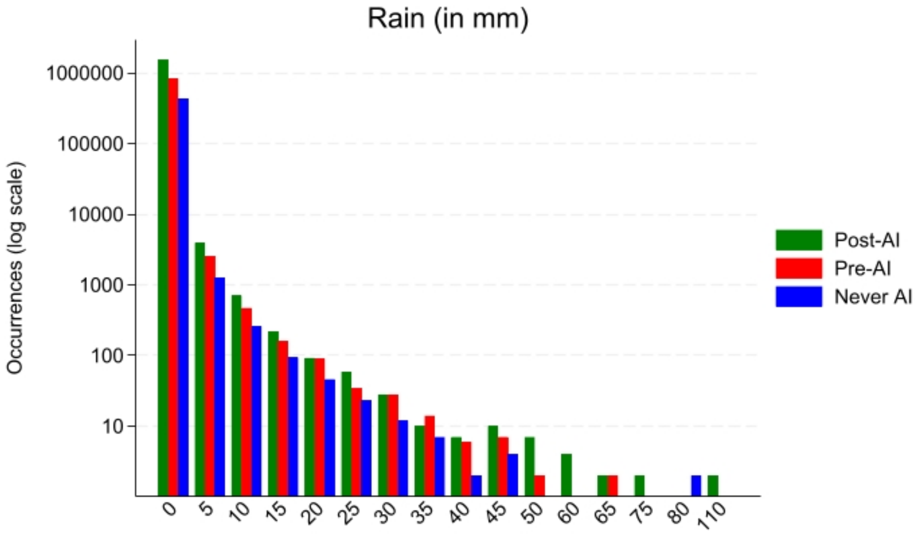
Figure D.9: Distribution of Oxido-Reduction Potential (ORP) values



Notes. Observations for redox values are at the hour-level.

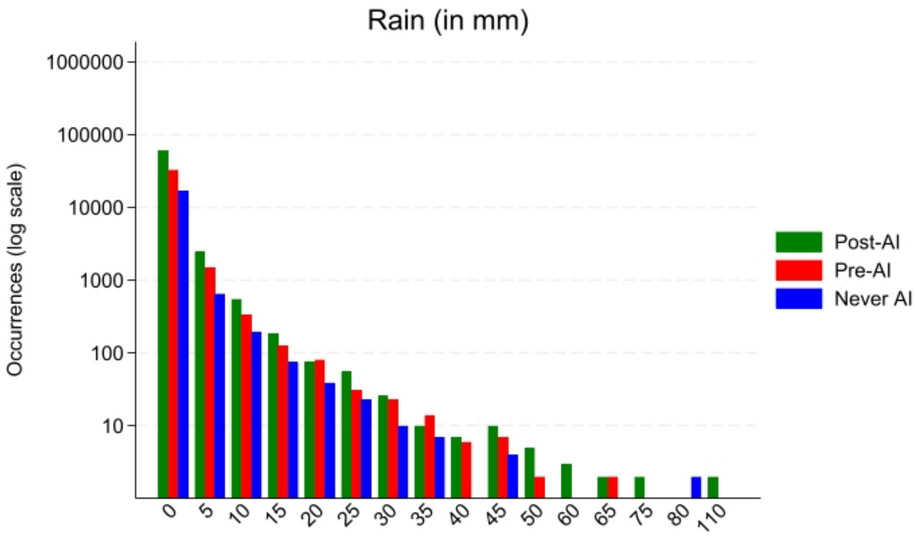
D.8 Rainfall Distribution

Figure D.10: Distribution of rainfall by hour



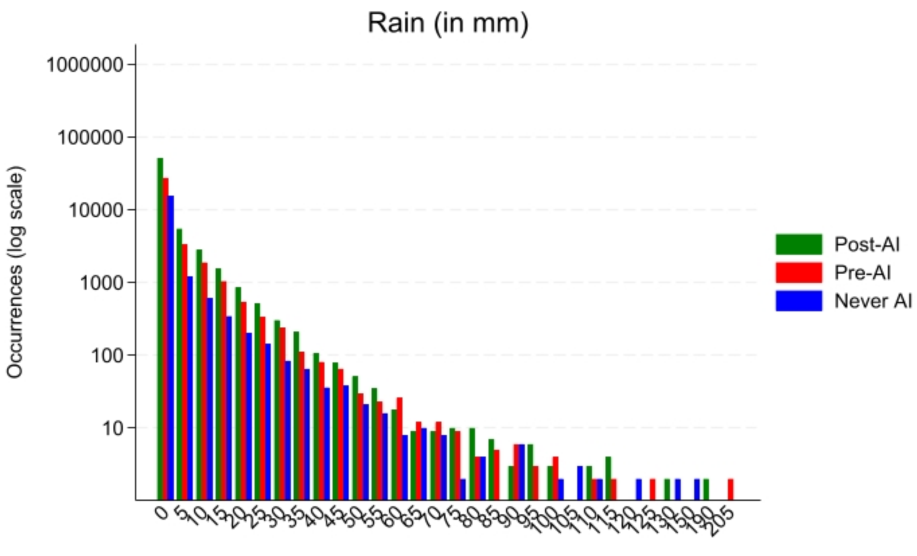
Notes. Observations for rainfall (in mm) are at the hour-level.

Figure D.11: Distribution of daily peak hourly rainfall



Notes. Observations for rainfall (in mm) are at the hour-level but plotted by day.

Figure D.12: Distribution of rainfall by day

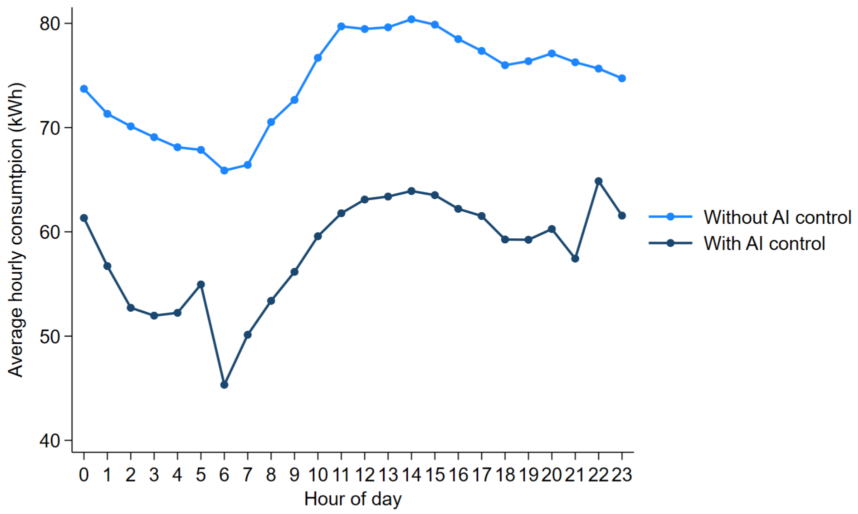


Notes. Observations for rainfall (in mm) are at the day-level.

E Effect of AI on electricity consumption and carbon footprint

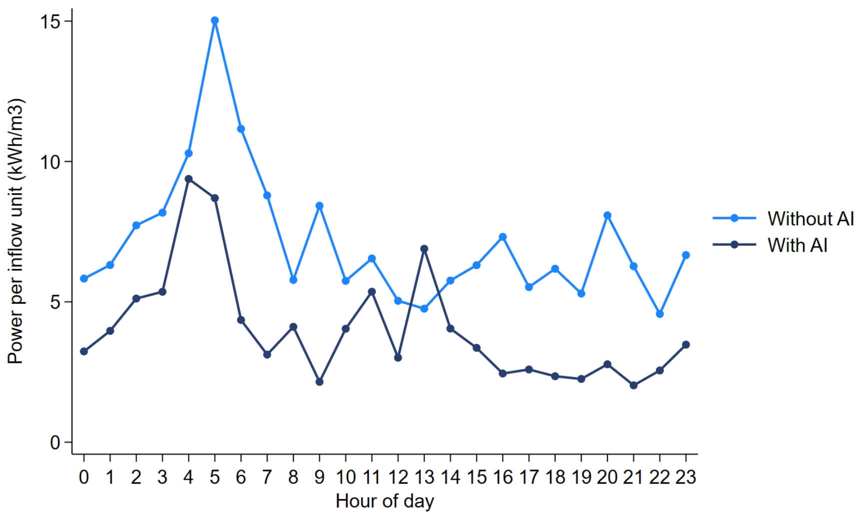
E.1 Descriptive analysis on electricity consumption and efficiency

Figure E.1: Hourly electricity consumption with and without AI control



Notes.

Figure E.2: Hourly electricity efficiency with and without AI control



Notes.

E.2 Estimator comparison

E.2.1 Daily level

Table E.1: Daily effects comparing DiD estimators

	TWFE-OLS (Std. Error)	De Chaisemartin-D'Haultfoeuille (Std. Error)
Electricity consumption	-0.044***	-0.015*
	(0.007)	(0.015)
Carbon footprint	-0.044***	-0.027*
	(0.007)	(0.016)
Electricity Cost	-0.05***	-0.044**
	(0.009)	(0.022)
Observations	93,779	
Number of plants	164	

Notes. This table reports the estimated impact of AI usage on daily electricity consumption expressed in log values at the plant level. We compare a standard two-way fixed effects (TWFE) estimator, with the average cumulative total effect per plant estimated over 15 days with de Chaisemartin and D'Haultfoeuille (2024). Effect on cost is obtained controlling for the mean individual weekly price. Standard errors are clustered at the plant level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

E.2.2 Weekly level

Table E.2: Weekly effects comparing DiD estimators

	TWFE-OLS (Std. Error)	De Chaisemartin-D'Haultfoeuille (Std. Error)
Electricity consumption	-0.044***	-0.054***
	(0.009)	(0.017)
Carbon footprint	-0.041***	-0.06***
	(0.009)	(0.018)
Electricity Cost	-0.052***	-0.082***
	(0.012)	(0.017)
Observations	13,708	
Number of plants	164	

Notes. This table reports the estimated impact of AI usage on weekly electricity consumption expressed in log values at the plant level. We compare a standard two-way fixed effects (TWFE) estimator, with the average cumulative total effect per plant estimated over 10 weeks with de Chaisemartin and D'Haultfoeuille (2024). Effect on cost is obtained controlling for the mean individual weekly price. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

E.2.3 Monthly level

Table E.3: Monthly effects comparing DiD estimators

	TWFE-OLS (Std. Error)	De Chaisemartin-D'Haultfoeuille (Std. Error)
Electricity consumption	-0.05***	-0.03
	(0.011)	(-0.022)
Carbon footprint	-0.046***	-0.044*
	(0.011)	(0.025)
Electricity Cost	-0.063***	-0.073***
	(0.01)	(0.027)
Observations	3,390	
Number of plants	164	

Notes. This table reports the estimated impact of AI usage on monthly electricity consumption expressed in log values at the plant level. We compare a standard two-way fixed effects (TWFE) estimator, with the average cumulative total effect per plant estimated over 3 months with de Chaisemartin and D'Haultfoeuille (2024). Effect on cost is obtained controlling for the mean individual weekly price. Standard errors are clustered at the plant level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

E.3 Absolute effects

Table E.4: Absolute weekly effects - AI usage

	TWFE-OLS (Std. Error)	De Chaisemartin-D'Haultfoeuille (Std. Error)
Electricity consumption	-314.9***	-606.8***
	(97.8)	(233.2)
Carbon footprint	11.3	-22.8
	(10.5)	(18.9)
Electricity Cost	-73.7*	-199.4**
	(38.5)	(87.9)
Observations	13,708	
Number of plants	164	

Notes. This table reports the estimated impact of AI usage on monthly electricity consumption at the plant level. We compare a standard two-way fixed effects (TWFE) estimator, with the average weekly cumulative total effect per plant estimated over 10 weeks with de Chaisemartin and D'Haultfoeuille (2024). Absolute effects are expressed in kilowatt-hours (kWh) for electricity consumption, kgCO_2e for the carbon footprint, and euros for the electricity cost. Effect on cost is obtained controlling for the mean individual weekly price. Standard errors are clustered at the plant level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F Conceptual Framework

F.1 Environment

Consider a set of wastewater treatment plants (or any industrial facility with an energy-intensive input) indexed by $i = 1, \dots, N$ operating over periods $t = 1, \dots, T$. Each plant must meet a compliance target (in this context, adequate aeration of incoming wastewater) and is characterized by a scale parameter L_i (its design flow rate). Achieving the target requires an amount of aeration that depends on plant scale and on stochastic operating conditions.

Required aeration. Let $A_i := A(L_i)$ denote the baseline aeration requirement of plant i under average operating conditions. Actual conditions (influent load, temperature, weather) introduce a stochastic "difficulty shifter" χ_{it}, so that the realized requirement is

$$R_{it} = A_i \cdot g(\chi_{it}) + \varepsilon_{it}, \tag{5}$$

where $g(\cdot)$ is increasing, $\mathbb{E}[g(\chi_{it})] = 1$, and ε_{it} is idiosyncratic noise with $\mathbb{E}[\varepsilon_{it} \mid \chi_{it}] = 0$[30]. The plant operator observes an information set $\mathcal{I}_{it}$ and must choose an aeration setpoint a_{it} before R_{it} is realized.

F.2 Decision Problem: Asymmetric Loss and Price

Cost structure. The operator faces: (i) an energy cost $p_{it}a_{it}$, where p_{it} is the electricity price, and (ii) a non-monetary loss from deviations between chosen aeration a_{it} and required aeration R_{it}. We model this loss as an asymmetric piecewise-linear function:

$$\ell(a, R) = \phi \cdot (a - R)_+ + \psi \cdot (R - a)_+, \quad \psi > \phi > 0, \tag{6}$$

where $(x)_+ = \max\{x, 0\}$. The interpretation:

- **Overshoot** ($a > R$): excess aeration wastes energy (cost ϕ per unit).
- **Undershoot** ($a < R$): insufficient aeration risks non-compliance, effluent violations, fines (cost ψ per unit, $\psi > \phi$).

Objective. The operator solves:

$$\min_{a \geq 0} \mathbb{E}\left[p_{it}a + \ell(a, R_{it}) \mid \mathcal{I}_{it}\right]. \tag{7}$$

Optimal decision rule. Let $F_{R|\mathcal{I}}$ denote the CDF of R_{it} conditional on $\mathcal{I}_{it}$. The first-order condition is:

$$p_{it} + \phi \cdot \Pr(R_{it} < a^* \mid \mathcal{I}_{it}) - \psi \cdot \Pr(R_{it} > a^* \mid \mathcal{I}_{it}) = 0. \tag{8}$$

[30]We implicitly restrict attention to shock realizations such that $R_{it} > 0$; since $A_i\, g(\chi_{it}) > 0$ and ε_{it} represents small measurement-level noise, this is innocuous.

Rearranging, we get:

$$F_{R|\mathcal{I}}(a^*) = \frac{\psi - p_{it}}{\phi + \psi}. \tag{9}$$

Therefore, we define the critical probability:

$$\tau(p_{it}) := \frac{\psi - p_{it}}{\phi + \psi}. \tag{10}$$

where $\tau(p_{it}) \in (0, 1)$ requires $p_{it} < \psi$, i.e. the electricity price must be below the unit cost of non-compliance, which we assume holds throughout.

Then the optimal setpoint is:

$$a^*_{it} = F^{-1}_{R|\mathcal{I}_{it}}\big(\tau(p_{it})\big).$$

Remark. When $p_{it} = 0$, $\tau = \psi/(\phi+\psi) > 1/2$, so the setpoint exceeds the median: the operator "over-provisions" to guard against costly undershoots. Higher prices p_{it} reduce τ, lowering the margin.

F.3 Artificial Intelligence as Information Refinement

Pre-AI information. Before AI adoption, the operator relies on a baseline information set $\mathcal{I}^{\text{pre}}_{it}$ (simple heuristics, historical averages, limited instrumentation). The predictive distribution of R_{it} has mean μ_{it} and dispersion θ^{pre}_{it}.

Post-AI information. AI systems (sensor fusion, machine learning, real-time forecasting) provide a refined information set $\mathcal{I}^{\text{AI}}_{it}$. We model this as a mean-preserving contraction (or Blackwell-more-informative experiment (Blackwell, 1953)):

$$\mathbb{E}[R_{it} \mid \mathcal{I}^{\text{AI}}_{it}] = \mathbb{E}[R_{it} \mid \mathcal{I}^{\text{pre}}_{it}] = \mu_{it}, \quad \text{Var}[R_{it} \mid \mathcal{I}^{\text{AI}}_{it}] < \text{Var}[R_{it} \mid \mathcal{I}^{\text{pre}}_{it}].$$

Denote $\theta^{\text{AI}}_{it} < \theta^{\text{pre}}_{it}$.

Assumption A1 (Location-scale family). For tractability, assume:

$$R_{it} = \mu_{it} + \theta_{it} \cdot Z, \quad Z \sim F_Z,\ \mathbb{E}[Z] = 0,\ \text{Var}(Z) = 1[31]. \tag{11}$$

Then:

$$a^*_{it} = \mu_{it} + \theta_{it} \cdot q_{\tau(p_{it})}(Z), \tag{12}$$

where $q_\tau(Z) = F_Z^{-1}(\tau)$ is the τ-quantile of Z. AI reduces θ_{it}, directly lowering the "safety margin" $\theta_{it} \cdot q_\tau$.

[31] The variance of Z is supposed to be equal to 1 without loss of generality.

Assumption A2 (Operating regime). We maintain two conditions throughout: (i) $\mathrm{med}(Z) = 0$ (satisfied for example if F_Z is symmetric), so that $q_\tau(Z) > 0$ if and only if $\tau > 1/2$; and (ii) $p_{it} < (\psi - \phi)/2$ for all i, t, which implies $\tau(p_{it}) > 1/2$ and hence a strictly positive safety margin $\theta_{it}\, q_{\tau(p_{it})} > 0$. Condition (ii) states that electricity is cheap relative to the asymmetry of the compliance loss, a natural assumption in our set-up. Note that (ii) is stronger than the original condition $p_{it} < \psi$ required for $\tau \in (0, 1)$.

F.4 Testable Implications

We derive five empirical predictions from the model, indexed as Implications 1–5.

Implication 1: Average Energy Savings

Prediction. AI adoption reduces expected aeration and energy consumption.

Proof. From (12):

$$\mathbb{E}[a_{it}^{\mathrm{AI}}] = \mathbb{E}[\mu_{it}] + \mathbb{E}[\theta_{it}^{\mathrm{AI}}] \cdot q_\tau, \quad \mathbb{E}[a_{it}^{\mathrm{pre}}] = \mathbb{E}[\mu_{it}] + \mathbb{E}[\theta_{it}^{\mathrm{pre}}] \cdot q_\tau.$$

Since $\theta_{it}^{\mathrm{AI}} < \theta_{it}^{\mathrm{pre}}$ and, by Assumption A2, $q_\tau > 0$:

$$\mathbb{E}[a_{it}^{\mathrm{AI}}] < \mathbb{E}[a_{it}^{\mathrm{pre}}].$$

Energy consumption $E_{it} = \kappa \cdot a_{it}$ (with $\kappa > 0$), so $\mathbb{E}[E_{it}^{\mathrm{AI}}] < \mathbb{E}[E_{it}^{\mathrm{pre}}]$. □

Implication 2: Heterogeneity by Inflow Level

Prediction. Energy savings are larger (in absolute terms) for low flow rate levels (low L_i).

Mechanism. The prediction rests on a single assumption about primitives: baseline forecast uncertainty is decreasing in plant scale,

$$\frac{\partial \theta_i^{\mathrm{pre}}}{\partial L_i} < 0,$$

reflecting that larger plants operate more stable processes (dampened inflow variability through larger buffer volumes, better pre-AI instrumentation, dedicated operating staff). Define the energy saving:

$$S_i := \mathbb{E}[E_i^{\mathrm{pre}}] - \mathbb{E}[E_i^{\mathrm{AI}}] = \kappa \cdot (\theta_i^{\mathrm{pre}} - \theta_i^{\mathrm{AI}}) \cdot q_\tau.$$

If AI reduces dispersion proportionally ($\theta_i^{\mathrm{AI}} = k \cdot \theta_i^{\mathrm{pre}}$, $k < 1$), then:

$$S_i = \kappa \cdot (1 - k) \cdot \theta_i^{\mathrm{pre}} \cdot q_\tau,$$

so that $\partial S_i / \partial L_i < 0$: absolute savings are larger for small plants. □

Remark. The prediction extends to percentage savings under a mild additional condition. Writing the relative saving as

$$\frac{S_i}{\mathbb{E}[E_i^{\text{pre}}]} = \frac{(1-k)\,(\theta_i^{\text{pre}}/\mu_i)\,q_\tau}{1+(\theta_i^{\text{pre}}/\mu_i)\,q_\tau},$$

which is strictly increasing in the ratio $\theta_i^{\text{pre}}/\mu_i$, a sufficient condition is that the *coefficient of variation* of required aeration is decreasing in L_i, i.e. small plants face not only higher absolute but also higher relative uncertainty (plausible, since smaller facilities typically operate with sparser instrumentation and older sensor equipment).

Implication 3: AI Creates and Amplifies Price Responsiveness

Prediction. AI adoption generates price responsiveness where pre-AI operations exhibit none, enabling temporal reallocation of energy use toward low-price periods.

Setup. Partition time into high-price periods (p^H) and low-price periods ($p^L < p^H$), with average price $\bar{p} = \lambda p^H + (1-\lambda)p^L$, $\lambda \in (0,1)$.

Pre-AI behavior. Without real-time optimization capability, the pre-AI operator is constrained to a single setpoint held fixed across price periods. Because the price enters the objective linearly, the optimal constrained setpoint solves (8) evaluated at the average price $\bar{p}$, i.e. $F_R(a^{\text{pre}}) = \tau(\bar{p})$:

$$a^{\text{pre}} = \mu + \theta^{\text{pre}} \cdot q_{\tau(\bar{p})}, \qquad \frac{\partial a^{\text{pre}}}{\partial p_{it}} = 0. \tag{13}$$

Post-AI behavior. The AI system continuously adjusts the setpoint to the prevailing real-time electricity price:

$$a_{it}^{\text{AI}} = \mu + \theta^{\text{AI}} \cdot q_{\tau(p_{it})}, \qquad \frac{\partial a^{\text{AI}}}{\partial p_{it}} = -\frac{\theta^{\text{AI}}}{(\phi+\psi)\,f_Z(q_\tau)} < 0. \tag{14}$$

Part (i) - Existence of price elasticity. From (10), $\partial\tau/\partial p = -1/(\phi+\psi) < 0$. Since $q_\tau = F_Z^{-1}(\tau)$ is strictly increasing, $\partial a^{\text{AI}}/\partial p < 0$, while $\partial a^{\text{pre}}/\partial p = 0$. AI strictly creates price elasticity. □

Part (ii) - Temporal reallocation. Define the reallocation gain as the energy saving in high-price periods relative to the flat pre-AI baseline:

$$\Delta E^H := \kappa\big(a^{\text{pre}} - a^{\text{AI}}(p^H)\big) = \kappa\Big[\theta^{\text{pre}}\,q_{\tau(\bar{p})} - \theta^{\text{AI}}\,q_{\tau(p^H)}\Big]. \tag{15}$$

Since $p^H > \bar{p}$ implies $\tau(p^H) < \tau(\bar{p})$, hence $q_{\tau(p^H)} < q_{\tau(\bar{p})}$, we decompose:

$$\Delta E^H = \underbrace{\kappa\,(\theta^{\text{pre}} - \theta^{\text{AI}})\,q_{\tau(\bar{p})}}_{\text{(a) uncertainty reduction}} + \underbrace{\kappa\,\theta^{\text{AI}}\,\big(q_{\tau(\bar{p})} - q_{\tau(p^H)}\big)}_{\text{(b) price response}} > 0. \tag{16}$$

Both terms are strictly positive: term (a) reflects the average energy saving from reduced forecast uncertainty (Implication 1); term (b) is the additional saving from active setpoint adjustment to real-time prices, which is zero pre-AI by construction and strictly positive post-AI. Hence:

$$\Delta E^H\big|_{\text{AI}} > \Delta E^H\big|_{\text{pre-AI}} = 0.$$

□

Implication 4: Overshoot Magnitude and Threshold Exceedances

Prediction. AI adoption leaves the ex-ante frequency of overshoot events ($a_{it} > R_{it}$) unchanged, but (i) reduces their conditional magnitude, and (ii) reduces the frequency of exceedances of any fixed size.

Proof. Part (i) — Frequency invariance and magnitude reduction. From (9), the ex-ante overshoot probability is

$$\Pr(a_{it}^* > R_{it} \mid \mathcal{I}_{it}) = \tau(p_{it}),$$

pinned down by the loss asymmetry and independent of θ_{it}: better information does not change how often the operator errs on the safe side, only by how much. Under (11), $a_{it}^* - R_{it} = \theta_{it}(q_\tau - Z)$, so the conditional overshoot magnitude is

$$\mathbb{E}[a_{it}^* - R_{it} \mid a_{it}^* > R_{it}] = \theta_{it} \cdot \mathbb{E}[q_\tau - Z \mid Z < q_\tau],$$

which is strictly increasing in θ_{it}. Hence $\theta_{it}^{\text{AI}} < \theta_{it}^{\text{pre}}$ implies smaller overshoots post-AI. □

Part (ii) — Fixed-threshold exceedances. Empirically, overshoots are measured against a fixed observable threshold (e.g., Oxido-Reduction Potential above a target level), not against the unobserved realized requirement R_{it}. For any fixed margin $c > 0$, the probability of an exceedance of size at least c is

$$\Pr(a_{it}^* - R_{it} > c) = \Pr\left(Z < q_\tau - \frac{c}{\theta_{it}}\right) = F_Z\left(q_\tau - \frac{c}{\theta_{it}}\right),$$

which is strictly increasing in θ_{it}. AI adoption therefore reduces the *frequency* of exceedances of any fixed magnitude, even though the unconditional overshoot probability τ is unchanged. Equivalently, in deterministic terms, the systematic margin falls by

$$\Delta a := a^{\text{pre}} - a^{\text{AI}} = (\theta^{\text{pre}} - \theta^{\text{AI}}) \cdot q_\tau > 0.$$

□

Implication 5: Dynamic Learning and Decreasing Returns

Prediction. If the AI model improves over time (θ_{it} decreasing in t), energy consumption declines gradually, exhibiting diminishing marginal gains.

Proof. Suppose $\theta_{it} = \theta_0 \cdot h(t)$, with $h'(t) < 0$ and $h''(t) > 0$ (convex decay of residual uncertainty, i.e. a concave cumulative learning curve).. Then:

$$a_{it}^* = \mu_{it} + \theta_0 \cdot h(t) \cdot q_\tau \quad \Rightarrow \quad \frac{\partial a_{it}^*}{\partial t} = \theta_0 \cdot h'(t) \cdot q_\tau < 0,$$

and:

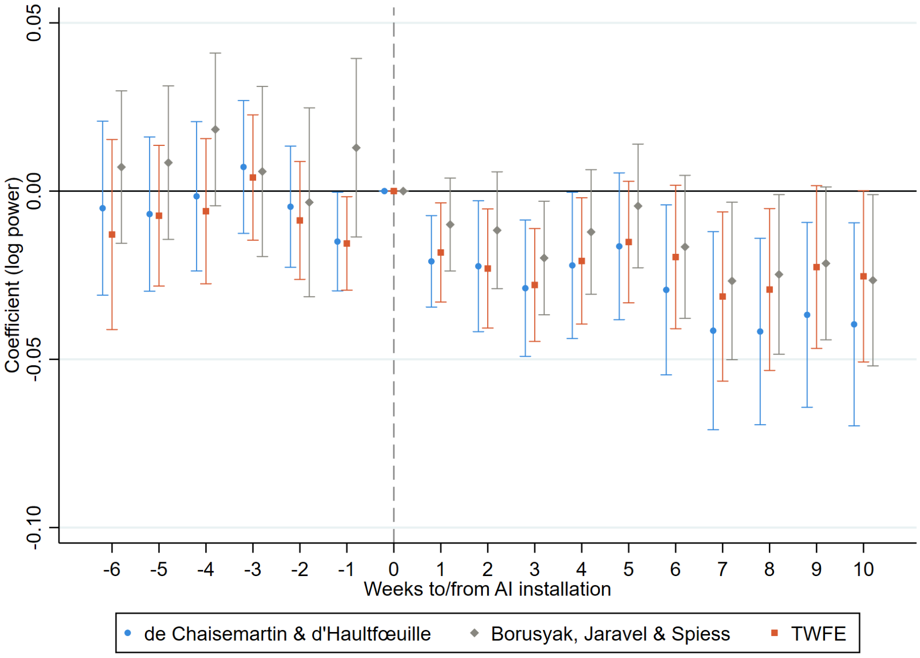
$$\frac{\partial^2 a_{it}^*}{\partial t^2} = \theta_0 \cdot h''(t) \cdot q_\tau > 0.$$

Thus, aeration (and energy) decrease over time at a decelerating rate. □

G Robustness checks

G.1 Event studies using different DiD estimators

Figure G.1: Event studies, Electricity consumption



Notes. This figure presents the effect of AI deployment on the electricity consumption of WWTP using the robust dynamic difference-in-differences estimators introduced in Borusyak, Jaravel and Spiess (2024) and de Chaisemartin and D'Haultfoeuille (2024), and a standard two-way fixed effects regression model. Data are are the weekly level and cover a period up to 10 weeks after AI installation.

G.2 Keeping only exogenous failures of AI

Table G.1: Effects on weekly electricity consumption, carbon footprint and costs

	AI usage	Treated	AI installed
Electricity Consumption			
	-0.044***	-0.033***	-0.03***
	(0.014)	(0.011)	(0.01)
Carbon footprint			
	-0.049***	-0.037***	-0.033***
	(0.016)	(0.012)	(0.011)
Electricity cost			
	-0.069***	-0.052***	-0.048***
	(0.018)	(0.012)	(0.012)
Observations		10,544	
Number of plants		164	

Notes: We report the average cumulative total effect measured over 10 weeks using de Chaisemartin and D'Haultfoeuille (2024). Electricity consumption, carbon footprint, and electricity cost are expressed in log values. The definition of the measure of AI use differs across columns. Effect on electricity cost is obtained controlling for the mean individual weekly electricity price. Standard errors are clustered at the plant level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G.3 Rebound Effect

Table G.2: Rebound Effect

	Electricity consumption		Carbon footprint		Electricity Cost	
	(1)	(2)	(3)	(4)	(5)	(6)
AI usage	-0.056***	-0.042***	-0.057***	-0.044***	-0.050***	-0.034**
	(0.010)	(0.012)	(0.010)	(0.012)	(0.014)	(0.016)
AI installed	0.028**	0.015	0.037***	0.024*	-0.006	-0.022
	(0.013)	(0.014)	(0.013)	(0.014)	(0.016)	(0.018)
Endogenous AI failures		0.016*		0.016*		0.019*
		(0.008)		(0.008)		(0.010)
Observations	13,697					
Number of plants	164					

Notes. This table reports the estimated impact of AI pilotage and AI implementation on daily electricity consumption, carbon footprint, and electricity cost, expressed in log values, at the plant level. All specifications include plant and week fixed effects with standard errors clustered at the plant level. Columns 1, 3, 5 exclude the AI outage control; columns 2, 4, 6 add *Endogenous AI failures* as a control variable to account for periods of system disruption created by either the plant management or the AI team. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G.4 Effects of AI by adoption wave

Table G.3: Effects of AI adoption by wave

	First wave		Second wave	
	dCdH	TWFE	dCdH	TWFE
Average total effect	-0.060		-0.047**	
	(0.042)		(0.018)	
TWFE coefficient		-0.046**		-0.049***
		(0.015)		(0.012)
Placebo test (p-value)	0.347		0.618	
Joint effects test (p-value)	0.444		0.065	
Observations	6,496	6,496	8,061	8,061
Number of plants	65	65	124	124

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the plant level in parentheses. dCdH refers to the de Chaisemartin and D'Haultfoeuille (2024) estimator. The dependent variable is log power consumption, and the independent variable is the AI usage share of time. Each wave subsample includes never-treated plants as controls.

G.5 Controlling for inflow

Table G.4: Average cumulative total effect per plant

	Estimate	Std. Error
Electricity consumption	-0.049***	0.017
Carbon footprint	-0.056***	0.019
Electric costs	-0.079***	0.019

Notes. This table reports the average cumulative total effect measured over 10 weeks estimated with de Chaisemartin and D'Haultfoeuille (2024) controlling for the inflow level. Effect on electricity cost is obtained controlling for the mean individual weekly electricity price. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G.6 Without Never Treated from the counterfactual

Table G.5: Average cumulative total effect per plant

	Estimate	Std. Error
Electricity consumption	-0.045***	0.017
Carbon footprint	-0.05***	0.019
Electricity cost	-0.075***	0.019

Notes. This table reports the average cumulative total effect measured over 10 weeks estimated with de Chaisemartin and D'Haultfoeuille (2024) by removing plants that were never treated from the counterfactual group. Effect on electricity cost is obtained controlling for the mean individual weekly electricity price. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G.7 Keeping only optimized control mode in the counterfactual

Table G.6: Average cumulative total effect per plant

	Estimate	Std. Error
Electricity consumption	-0.052***	0.017
Carbon footprint	-0.056***	0.025
Electricity cost	-0.078***	0.021

Notes. This table reports the average cumulative total effect measured over 4 weeks estimated with de Chaisemartin and D'Haultfoeuille (2024) by removing observations daily observations where the most important control mode was the P0 "local mode". Effect can only be observed through 4 weeks due to the lack counterfactual data. Effect on electricity cost is obtained controlling for the mean individual weekly electricity price. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table G.7: TWFE

	Estimate	Std. Error
Electricity consumption	-0.048***	0.009
Carbon footprint	-0.044***	0.009
Electricity cost	-0.061***	0.012

Notes. This table reports the effect measured with the standard TWFE estimator, by removing observations daily observations where the most important control mode was the P0 "local mode". Effect on electricity cost is obtained controlling for the mean individual weekly electricity price. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

H Heterogeneous AI impact

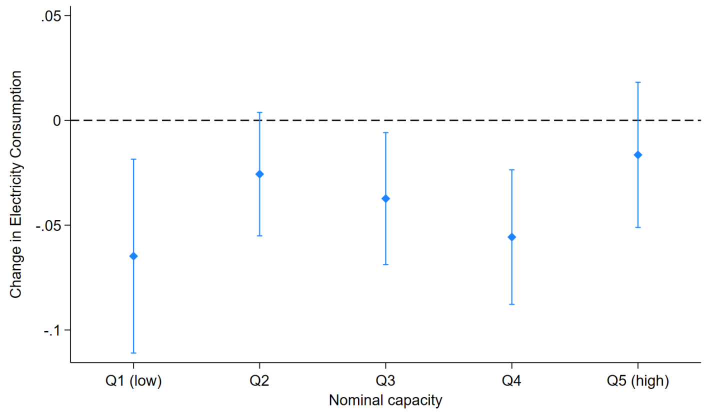
H.1 By plant

To explore cross-plant heterogeneity, we classify plants into quintiles based on their nominal capacity and average inflow size over the sample period. We the estimate the following TWFE regression intereacting AI use with these quintile indicators:

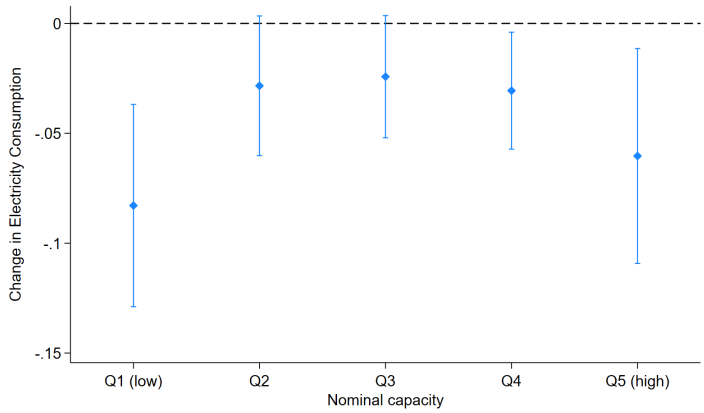
$$\ln(\text{Power}_{it}) = \sum_{q=1}^{5} \beta_q \left(\text{AI usage}_{it} \times \mathbb{1}\{i \in Q_q\}\right) + \alpha_i + \delta_t + \varepsilon_{it},$$

Figure H.1: AI impact by plant size - in relative value

(a) by Nominal Capacity



(b) by Average Inflow



Notes. This figure plots the coefficients and 95% confidence intervals of the interaction term between AI usage intensity and the quintile of nominal capacity, measured in People Equivalent (subfigure a), and average inflow (subfigure b) of each plant using a standard TWFE regression on the logarithm of electricity consumption.

H.2 By inflow

Table H.1: Heterogeneity by inflow: TWFE

	AI Usage	Highly Treated	Treated	Ever Treated
Electricity Consumption				
AI use	-0.112***	-0.100***	-0.098**	-0.087
	(0.040)	(0.038)	(0.039)	(0.053)
Inflow	0.059***	0.059***	0.059***	0.057***
	(0.012)	(0.012)	(0.012)	(0.014)
Inflow * AI use	0.016*	0.016*	0.016*	0.016
	(0.12)	(0.12)	(0.12)	(0.14)
Carbon footprint				
AI use	-0.114***	-0.100***	-0.098**	-0.085
	(0.039)	(0.037)	(0.038)	(0.052)
Inflow	0.059***	0.059***	0.058***	0.057***
	(0.012)	(0.012)	(0.012)	(0.014)
Inflow * AI use	0.016*	0.016*	0.016*	0.016
	(0.012)	(0.012)	(0.012)	(0.014)
Plant FE	170	170	170	170
Date-Hour FE	31’449	31’449	31’449	31’449
Observations	2’042’110	2’042’110	2’042’110	2’042’110

Note: Electricity Consumption, Carbon footprint and Inflows are expressed in log values. The definition of the measure of AI use differs indifferent columns. Data are at the hourly level. Fixed effects at the day-hour and id levels and SE clustering at the id level are included. *p<0.1; **p<0.05; ***p<0.01. R^2 are at 79.7% for electricity consumption and at 86.6% for carbon emissions.

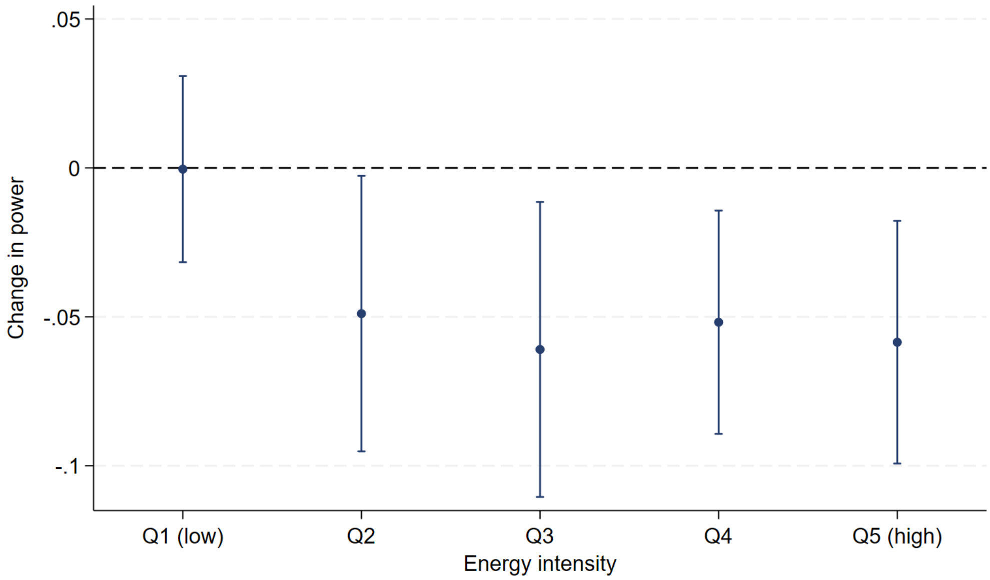
Table H.2: Energy intensity heterogeneity by inflow - TWFE

	Log(Energy intensity)
AI usage	-0.19^{**}
	(0.079)
Log(inflow)	-1.06^{***}
	(0.09)
Log(inflow) * AI usage	0.034^{*}
	(0.018)
Observations	2,021,413
Number of plants	155

Notes: Energy intensity refers to the electricity consumption per unit of inflow. The specification include plant and date fixed effects. Standard errors are clustered at the plant level. Data are at the hourly level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

H.3 By energy intensity pre-AI installation

Figure H.2: Heterogeneous effects of AI usage on electricity consumption by quintile of energy intensity pre AI installation

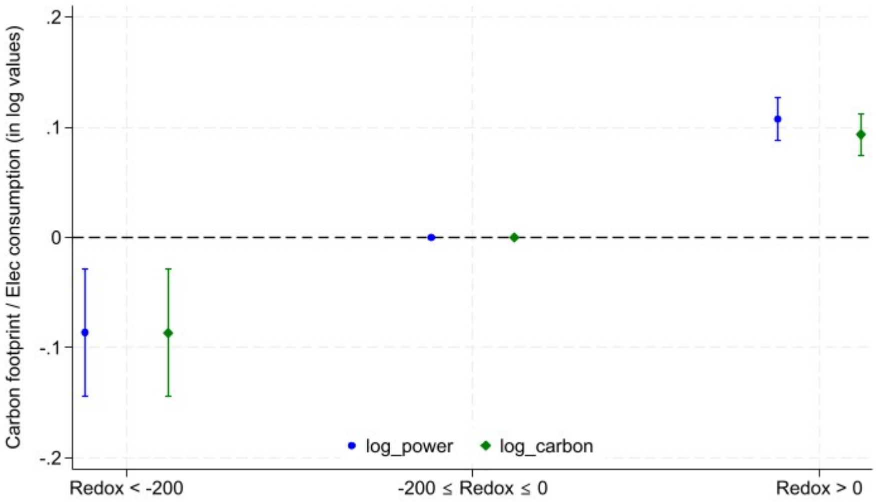


Notes. This figure reports the coefficients and 95% confidence intervals of the interaction between AI usage and pre-treatment energy intensity quintiles. Energy intensity is defined as electricity consumption per unit of inflow. Plants in the lowest quintile exhibit the lowest pre-treatment energy intensity, while plants in the highest quintile exhibit the highest energy intensity. We estimate a TWFE model with plant and time fixed effects using weekly data. Standard errors are clustered at the plant level.

I Oxido-Reduction Potential and AI

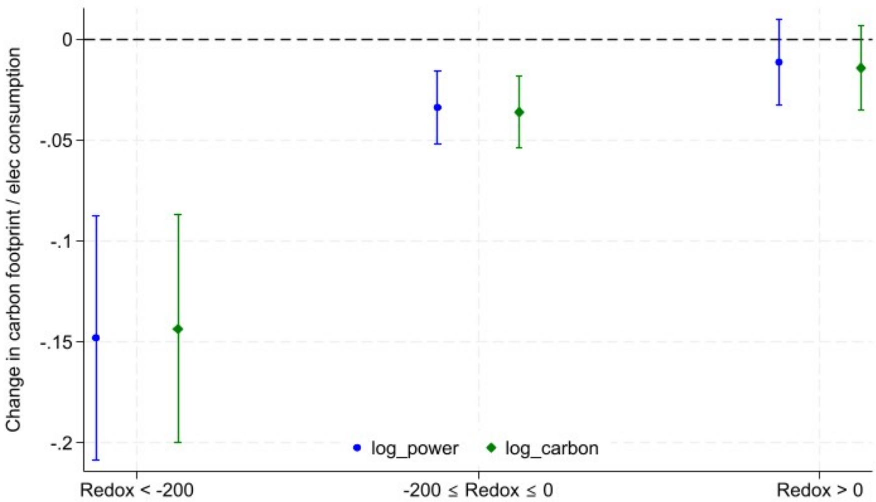
I.1 Empirical Results

Figure I.1: Heterogeneous baseline consumption depending on the ORP level



Notes. Electricity Consumption and Carbon footprint are expressed in log values. Redox between -200 and 0 mV is taken as the baseline. The definition of the measure of AI use differs indifferent columns. Fixed effects at the day and id levels and SE clustering at the id level are included. CI are at the 95% level.

Figure I.2: AI heterogeneous impact by Oxido-Reduction Potential (ORP) level



Notes. Electricity Consumption and Carbon footprint are expressed in log values. The definition of the measure of AI use differs in different columns. Fixed effects at the day and id levels and SE clustering at the id level are included. Confidence intervals are expressed at the 95 % level.

J Effluent Quality Analysis

J.1 The Nitrogen Removal Pathway

Nitrogen removal in wastewater treatment plants (WWTPs) relies on a two-stage biological process: nitrification followed by denitrification. These two processes are biochemically sequential yet operationally antagonistic, as they require fundamentally different redox conditions. Understanding their interplay is essential to rationalize both the levels of ammonium and nitrate observed in WWTP effluents and the channels through which AI-based process control can improve outcomes (Tchobanoglous and Eddy., 2014).

Nitrification. Nitrification is an aerobic, autotrophic process carried out by specialized bacteria that oxidize ammonium (NH_4^+) to nitrite (NO_2^-) and then to nitrate (NO_3^-):

$$NH_4^+ + \frac{3}{2}O_2 \xrightarrow{\textit{specialized bacteria}} NO_2^- + H_2O + 2\,H^+ \tag{17}$$

$$NO_2^- + \frac{1}{2}O_2 \xrightarrow{\textit{specialized bacteria}} NO_3^- \tag{18}$$

This process requires a sustained supply of dissolved oxygen (DO) and is sensitive to temperature, pH, and organic loading. The net reaction converts NH_4^+ into NO_3^-, so incomplete nitrification leaves residual ammonium in the effluent, while complete nitrification produces nitrate, which must in turn be removed by denitrification.

Denitrification. Denitrification is an anoxic, heterotrophic process by which facultative bacteria use nitrate as a terminal electron acceptor in the absence of oxygen, reducing it to dinitrogen gas:

$$NO_3^- \xrightarrow{-2e^-} NO_2^- \xrightarrow{-2e^-} NO \xrightarrow{-e^-} N_2O \xrightarrow{-e^-} N_2 \uparrow \tag{19}$$

This process requires a carbon source (typically the organic matter present in the influent) and, critically, the absence of dissolved oxygen, which would otherwise be preferentially used as the electron acceptor, outcompeting nitrate and shutting down denitrification.

The nitrification-denitrification trade-off. The core operational challenge in biological nitrogen removal is that these two processes require opposite aeration conditions. Nitrification demands sustained oxygenation, while denitrification requires anoxic zones. In practice, WWTPs implement alternating aerobic and anoxic phases through intermittent aeration strategies to satisfy both requirements within the same treatment train. A key challenge for the system is to access a fine dynamic optimum: enough aeration to drive complete nitrification of incoming NH_4^+, but not so much as to suppress the anoxic zones needed for subsequent denitrification.

J.2 AI and Nitrogen Removal

Under low-to-moderate ammonium loads, conventional rule-based controllers can maintain this balance without great difficulty. The nitrification capacity of the sludge is not saturated, and the anoxic volume in the reactor is sufficient to handle the nitrate produced. Effluent concentrations of both NH_4^+ and NO_3^- remain within acceptable bounds with relatively coarse aeration control.

The challenge of High Ammonium Loads. The management of activated sludge systems under high ammonium loads is inherently difficult, as conventional control systems typically respond by increasing aeration to prevent ammonium breakthrough (Xiong et al., 2025). While increasing aeration is a rational local response to rising influent loads, it is often counterproductive at the system level because over-aeration extends the aerobic phase at the expense of the anoxic phase, thereby suppressing the denitrification process (Raboni et al., 2020). The inhibitory effect of dissolved oxygen (DO) on denitrification is extensively documented (Oh and Silverstein, 1999; Raboni et al., 2020). Under conditions of excess aeration, oxygen carries over through recirculated nitrified water, where it acts as a more energetically favorable electron acceptor than nitrate, effectively shutting down denitrification (Qin et al., 2023). This leads to a scenario where nitrate accumulates in the effluent even if nitrification remains incomplete, resulting in the simultaneous elevation of both ammonium and nitrate levels. Conventional DO feedback control has been shown to perform poorly under high and variable ammonium loading because it is responding only after oxygen depletion is observed, rather than anticipating nitrogen dynamics (Åmand, Olsson and Carlsson, 2013). In full-scale plants, this issue is exacerbated by chemical analysis delays that can reach several hours or days, forcing operators to rely on manual adjustments or conservative, energy-intensive strategies. These limitations have driven a growing body of literature focused on advanced aeration control and provide the operational context in which AI-based systems can yield significant performance gains and reductions in operational expenditure (Xiong et al., 2025; Croll et al., 2023; Chen et al., 2021).

The dynamic aeration optimization channel. AI-based process control can be expected to improve effluent nitrogen quality through dynamic aeration optimization. Rather than responding reactively to a single sensor reading, AI controllers can integrate information from multiple sensors, hence AI controllers can learn the optimal phase durations as a function of real-time influent characteristics, temperature, and sludge activity, adapting dynamically rather than following fixed time-based cycles. It can also have a pro-active rather than simply reactive attitude toward nitrogen loads to anticipate loading variations and adjust aeration setpoints ahead of time. This allows the system to maintain the aerobic-anoxic balance across a wider range of operating conditions, including high-load episodes during which conventional controllers fail.

J.3 Empirical Results

The empirical findings reported below are consistent with this biochemical picture. The negative effect of AI adoption on both NH_4^+ and NO_3^- concentrations in effluents is the expected signature of improved joint optimization of the nitrification-denitrification cycle: AI reduces ammonium by improving nitrification completeness, and simultaneously reduces nitrate by preserving the anoxic conditions necessary for denitrification outcomes that are mechanistically linked rather than independent. The concentration of this effect in high-ammonium regimes further corroborates the mechanism: it is precisely when conventional controllers over-aerate and compromise denitrification that AI-based dynamic optimization yields the largest gains.

Table J.1: Effect of AI pilotage on effluent quality

	(1) Nitrate	(2) Ammonium	(3) Phosphate
AI usage	-0.508***	-0.292**	-0.030
	(0.114)	(0.117)	(0.031)
Constant	1.977***	1.738***	0.616***
	(0.049)	(0.051)	(0.012)
Plant FE	147	148	74
Date FE	969	969	604
Observations	20,269	20,636	8,484

Notes. This table presents the effect of AI usage on Nitrate (NO_3^-), Ammonium (NH_4^+), and Phosphate (PO_4^{3-}) concentrations using a standard two-way fixed effects regression model. Plant and date fixed effects are included in all specifications. Standard errors appear in parentheses and are clustered at plant level. Observations are at the day level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table J.2: Impact of AI on compliance with rejection limits

	(1) NH_4^+ compliance	(2) PO_4^{3-} compliance
AI usage	0.585***	-0.093
	(0.146)	(0.147)
Plant FE	116	52
Observations	15,754	5,713

Notes. This table reports estimates from conditional (fixed-effects) logistic regressions. Coefficients are expressed in log-odds. The dependent variable is a dummy equal to one when the samples respect the quality thresholds. Standard errors are obtained by bootstrap with 200 replications and are clustered at the plant level. The estimation relies on within-plant variation only. Plants with no within-plant variation in the compliance status are not included in the estimation. Observations are at the day level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table J.3: Quantile regressions of ammonium concentration on AI usage

Quantile	.1	.2	.3	.4	.5	.6	.7	.8	.9
AI usage	0.29***	0.24***	0.19***	0.15***	0.11**	0.05	-0.06	-0.29*	-0.71**
	(0.04)	(0.04)	(0.04)	(0.051)	(0.05)	(0.06)	(0.09)	(0.16)	(0.28)
Observations					20,815				

Notes. This table presents the effect of AI usage on ammonium (NH_4^+) concentrations using quantile regressions with plant fixed effects using the estimator of Machado and Silva (2019). Bootstrap standard errors clustered at plant level appear in parentheses. Observations are at the day level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

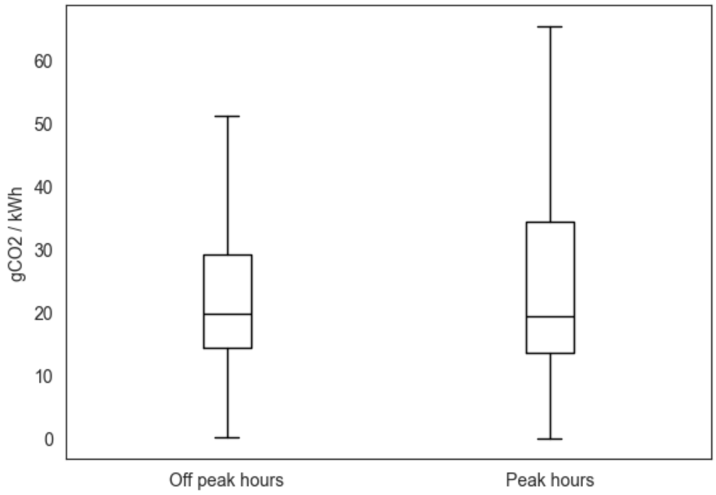
Table J.4: Effect of AI depending on ammonium concentration heterogeneity

	Dependent variable		
Ammonium decile	Nitrate (mg/L)	Redox (mV)	Power (kW/h)
D1 (low)	0.184	-7.810	-0.440
	(0.229)	(13.458)	(1.580)
D2	0.199	-17.802**	-1.465
	(0.232)	(8.949)	(1.966)
D3	-0.326*	-20.125***	-0.230
	(0.171)	(6.676)	(1.692)
D4	-0.599**	-31.411***	-1.655
	(0.236)	(8.239)	(1.233)
D5	-0.542***	-39.733***	-2.476**
	(0.143)	(7.148)	(1.088)
D6	-0.622***	-42.749***	-2.057*
	(0.192)	(8.309)	(1.185)
D7	-0.615***	-36.095***	-2.834**
	(0.147)	(5.365)	(1.430)
D8	-0.597***	-37.637***	-1.877
	(0.168)	(6.747)	(1.392)
D9	-0.872***	-39.411***	-2.613**
	(0.144)	(6.290)	(1.168)
D10 (high)	-1.271***	-57.903***	-2.149
	(0.167)	(6.878)	(1.517)
R^2	0.225	0.486	0.884
Plant FE	147	143	148
Date FE	966	956	969
Observations	20,024	19,009	20,636

Notes. This table reports the marginal effect of AI usage on Nitrate concentration (mg/L), redox (mV) and Power (kWh) depending on the concentration of ammonium. We use a standard two-way fixed effects regression, and report the coefficients of the interaction terms between AI usage and ammonium concentrations deciles. Clustered standard errors at the plant level are in parentheses. Observations are at the day level. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

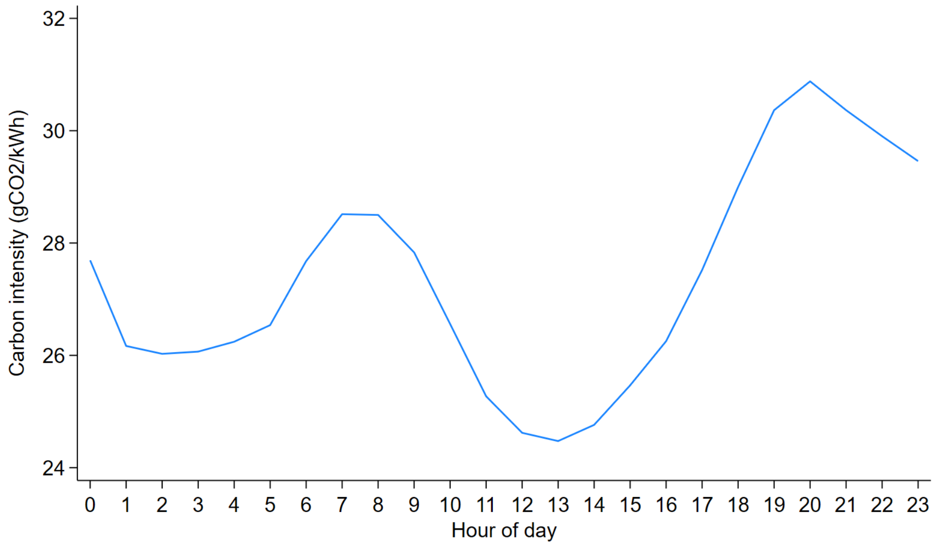
K Power reallocation between peak and off-peak hours

Figure K.1: Carbon intensity, Peak and Off-peak hours



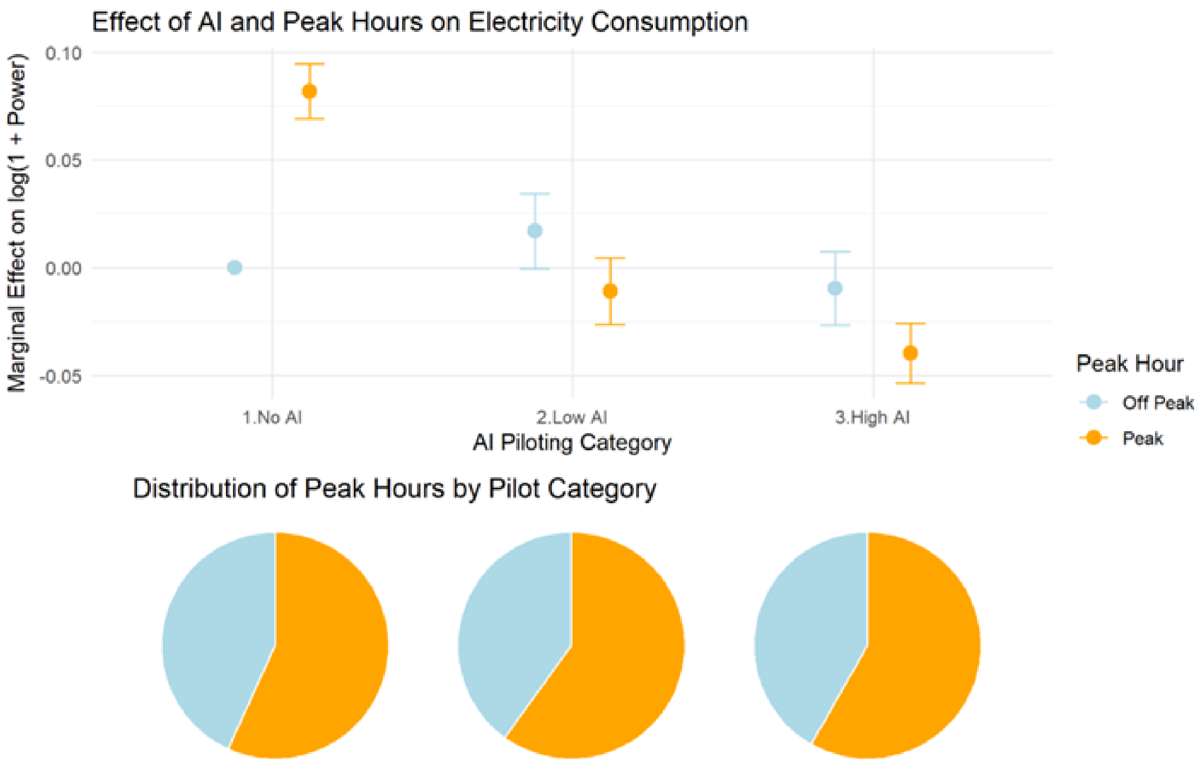
Notes. This figure shows boxplots of hourly carbon intensity (CO2 equivalent emissions in g/kWh) for off-peak and peak hours. Peak hours are hours from 5 AM to 10 PM with a higher electricity price compared to off-peak hours.

Figure K.2: Carbon intensity during the day



Notes.

Figure K.3: TWFE: Peak vs. Off-peak Hours

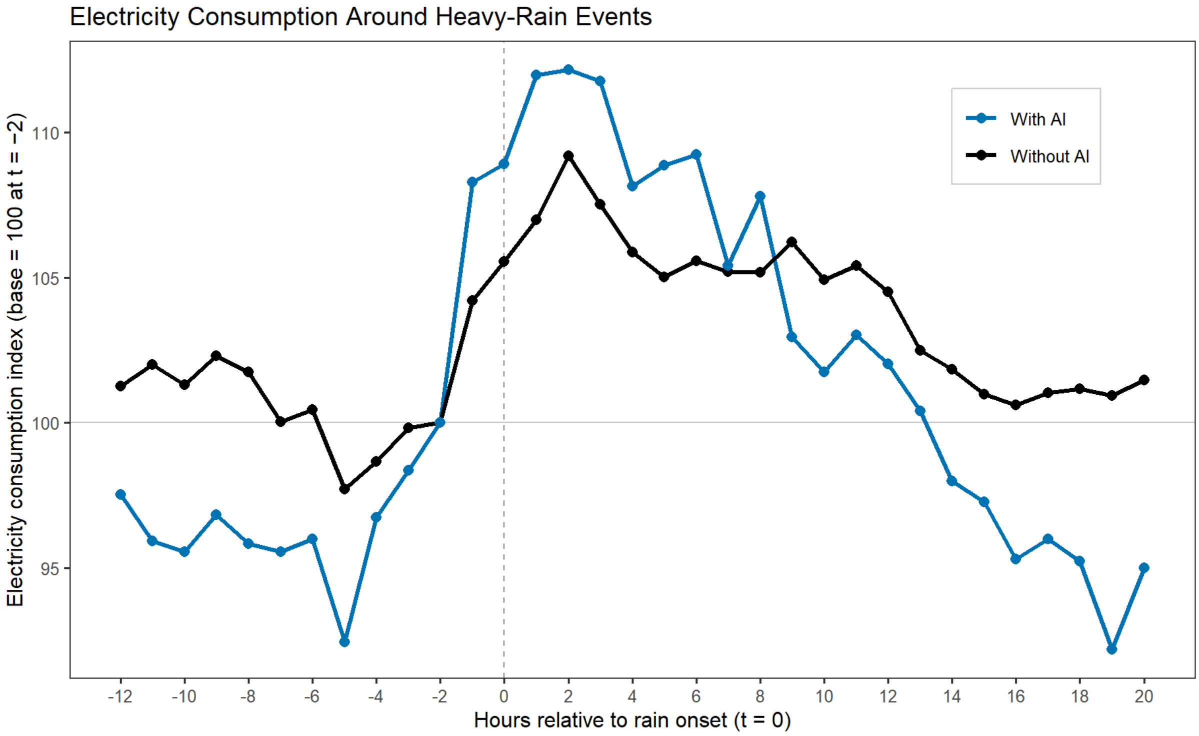


Notes. This figure shows boxplots of hourly carbon intensity (CO2 equivalent emissions in g/kWh) for off-peak and peak hours.

L Extreme Meteorological Events

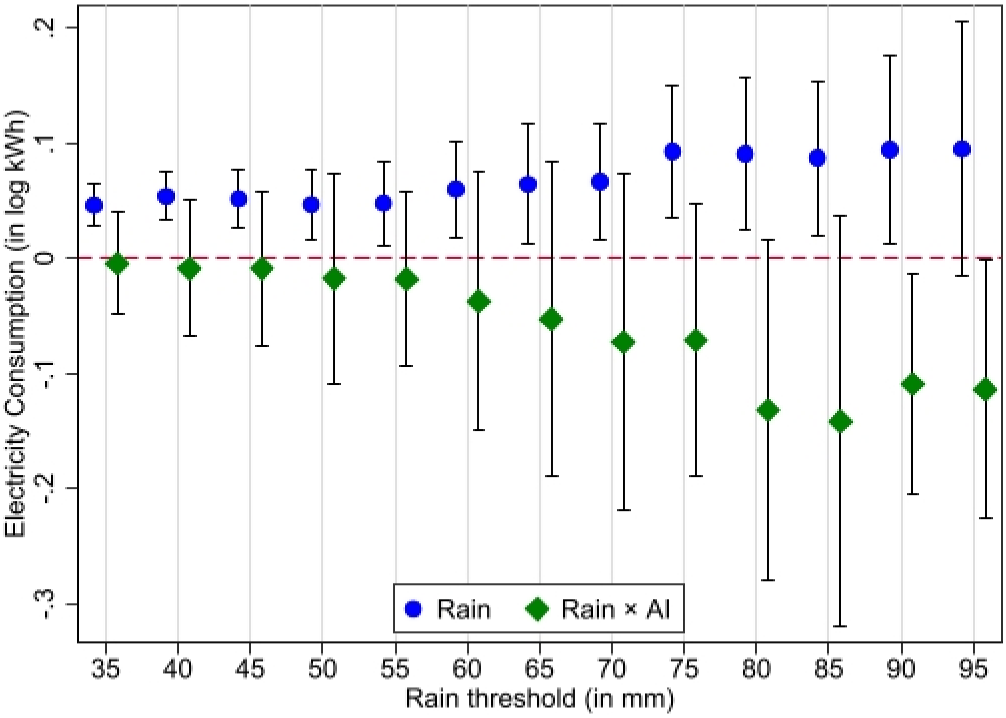
L.1 Consumption Profiles With and Without AI

Figure L.1: Electricity Consumption Around Heavy-Rain Events: AI vs. Non-AI Plants



Notes. This figure plots average electricity consumption around rain onset events (30-55 mm/h), separately for plants operating with and without AI monitoring. Each event is normalized to 100 at $t = -2$ hours before the high rainfall event. Residuals are purged of plant $\times$ hour-of-day, plant $\times$ day-of-week, and plant $\times$ rain-bin fixed effects to control for systematic differences in consumption patterns and concurrent rainfall intensity. "With AI" denotes plants for which more than 80% of hours in the 30 days prior to the event were under AI inference mode (P2); "Without AI" denotes plants with no AI exposure.

L.2 Intense Rainy Episode at the day-level



Thr.	35	40	45	50	55	60	65	70	75	80	85	90	95
IPW	10^2	10^2	10^2	10^2	10^2	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3

Figure L.2: Hourly Concentration Volume (hour-level)

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