Attention and Green Delivery*

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Abstract

We show that attention is a key determinant of household contributions to the green transition. Using transaction-level data from Singapore's largest online supermarket, we study a 'green delivery' option that reduces carbon emissions by consolidating routes but requires giving up scheduling flexibility. We find that households are less likely to adopt green delivery under environmental pressures: higher air pollution, elevated wet-bulb temperatures, and electricity price-cap events all reduce uptake. By contrast, nationwide sustainability campaigns sharply increase participation, functioning as salience shocks that redirect attention toward environmental goals. However, this salience effect is significantly attenuated under high environmental pressures. A behavioral inattention framework explains these patterns, showing how stress narrows attention to immediate comfort and cost, while salience cues restore focus on future environmental benefits. Our results highlight attention as a key mechanism in sustainable consumption.

Keywords: attention, cognitive scarcity, sustainability, green delivery, household behavior, environmental economics, pro-social behavior

JEL Classification: D12, D83, D91, Q54, Q58

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1 Introduction

Households are central to the low-carbon transition. Their everyday decisions about energy use, transportation, recycling, and consumption aggregate into outcomes that determine both the pace and the cost of climate mitigation. Yet household contributions remain limited even as concern about climate change is widespread. Since the seminal work of Wicker (1969), research has consistently shown that stated environmental attitudes often fail to translate into realized behavior. In financial contexts, Anderson and Robinson (2022) show using Swedish survey and administrative data that pro-environment households are no more likely to hold green assets. Similar patterns appear in energy and housing markets, where consumers underreact to information on energy efficiency or rely on simplified heuristics such as color-coded labels (Sejas-Portillo et al. 2025). A large-scale survey across 37 nations finds that purchase of household energy-saving products has a limited effect on energy consumption expenditure(Piao and Managi 2023). In this paper, we focus on the role of attention and consumer green choices.

A large literature shows that cognitive scarcity distorts decision-making (DellaVigna 2009; Gabaix 2019). Limited bandwidth has been linked to weaker financial capability, lower labor productivity, and poorer educational attainment. When individuals face stress, attention narrows toward immediate concerns (Allcott and Mullainathan 2010; Mullainathan and Shafir 2013). In the context of environmental risk, this narrowing shapes how households perceive and respond to changing conditions. Recent work shows that salience can heighten private protective behavior. Households are more likely to purchase insurance when air pollution worsens (Chang et al. 2018) or when extreme heat raises perceived risks (Agarwal et al. 2025). These findings suggest that environmental shocks can focus attention on self-protection and amplify demand for private risk-mitigation instruments.

Nonetheless, the same attentional mechanism may operate in the opposite direction for collective environmental actions. When environmental stress heightens immediate concerns, it can crowd out attention to longer-term or prosocial goals such as energy conservation or sustainable consumption. In this sense, insurance and environmental behaviors are two outcomes of a common attentional process. Both respond to environmental risk, but one reflects a shift toward private adaptation while the other requires public mitigation. Economic models of climate behavior emphasize that these responses may be substitutes rather than complements (Bayramoglu et al. 2018). If attention scarcity systematically reallocates effort from collective mitigation toward private protection, the aggregate consequences for the low-carbon transition could be substantial.

Understanding when environmental shocks trigger defensive adaptation rather than cooperative mitigation is therefore essential for designing policies that sustain household contributions to climate goals. Nonetheless, empirical evidence remains limited. Most studies rely on stated preferences, survey experiments, or investment decisions that only indirectly capture behavioral responses. We contribute by providing real-time evidence on revealed household behavior involving tangible trade-offs between private convenience and collective environmental benefit. Our analysis identifies how transient shocks to stress and salience influence household attention and whether these shifts reallocate effort from public mitigation to private adaptation.

Empirically, addressing this question is challenging along two dimensions. The first concerns data: real-time, high-frequency observations of pro-environmental choices that entail tangible trade-offs between private convenience and environmental benefit are scarce. The second is empirical design: it is difficult to obtain plausibly exogenous variation in the salience of environmental concerns. We overcome both challenges in the following ways. On the data front, we use unique administrative transaction-level records from RedMart, Singapore's leading online grocery platform, which capture household delivery choices at checkout. On the research design front, we combine these microdata with multiple sources of exogenous variation, including weather shocks, air quality, temporary electricity price caps, and government-led environmental campaigns that allow us to isolate shifts in salience and attention.

Singapore provides an especially suitable setting for this analysis. The country experiences frequent weather variability and recurrent air-quality shocks, and its electricity market features a transparent price cap that automatically activates under extreme conditions, heightening the salience of energy costs. In parallel, the government regularly organizes highly publicized environmental campaigns such as Clean & Green Singapore and Go Green SG, which generate sharp, short-lived increases in the visibility of sustainability concerns.[1] Together, these institutional features provide multiple, plausibly exogenous sources of variation that can be directly linked to household consumption choices in real time.

To study how attention shapes pro-environmental behavior, we rely on unique administrative data from Singapore's leading online grocer, RedMart. As Lazada's dedicated grocery platform, RedMart offers scheduled delivery of fresh produce and household essentials and serves as a major channel for online grocery purchases in Singapore. At

[1] Clean & Green Singapore is an annual national campaign launched in 1990 to promote environmental awareness, tree planting, and community-level participation in waste reduction and energy conservation. It is typically anchored by large-scale public events, exhibitions, and school programs coordinated by the National Environment Agency (NEA). Go Green SG is a more recent initiative, launched in 2022 as a whole-of-nation sustainability movement under Singapore's Green Plan 2030. It consolidates a month-long series of outreach activities across government agencies, firms, and communities, emphasizing everyday sustainable actions in areas such as energy, transport, and waste. Both campaigns attract extensive media coverage and social engagement, temporarily increasing the salience of environmental issues across households and firms.

checkout, customers choose among delivery slots that differ in convenience and cost. Some slots are labeled 'Less CO_2' because they enable logistics consolidation and reduce emissions. Importantly, the green label appears only once a slot has been pooled with at least one other order in the same area. Early buyers in a slot may not see the label, while later buyers do. These 'green delivery' options carry no financial incentive and differ only by the environmental label, providing a clean measure of willingness to trade off private convenience for environmental benefit.

Our dataset covers roughly 100,000 anonymized delivery orders between March 2023 and March 2025. About 60,000 orders display only standard slots, while 36,000 include at least one labeled 'Less CO_2'. We focus on this latter subset to analyze adoption behavior conditional on availability. For each order, we observe the full menu of delivery slots, the slot chosen, and detailed basket characteristics including expenditure, quantity, and weight. We augment these data with district-level weather conditions, high-frequency air-quality measures, temporary electricity price caps, and a hand-collected database of environmental campaigns. Together, these sources provide rich, quasi-experimental variation to examine how exogenous shocks to salience and attention influence household contributions to collective environmental goods in everyday consumption decisions.

We find three complementary mechanisms through which attention shapes sustainable behavior. First, the structure of the choice environment plays a central role. When a greater share of available slots is labeled as green, adoption rises sharply: a 10–percentage-point increase in green slot availability raises uptake by 5–6 percentage points. This shows that salience within the menu directly affects whether sustainability enters the consideration set. However, this sensitivity to choice architecture is moderated by household circumstances. High-value orders are 12 percentage points less likely to go green, and larger, more complex baskets systematically reduce adoption. These patterns suggest that when financial stakes are higher or cognitive load is greater, immediate convenience dominates environmental considerations, consistent with the idea that limited attention constrains sustainable decision-making.

Second, environmental stressors further deplete available attention and crowd out sustainable choices. Poor air quality (1 unit PSI increase) reduces green adoption by 0.1 percentage points, while heat-humidity stress (1 unit increase in wet-bulb temperature) lowers uptake by 4 percentage points (up to 21 percentage points across the observed range). Temporary electricity price-cap events reduce adoption by about 7 percentage points. Although these events do not alter the price of green delivery itself, they heighten public awareness of energy costs and shift attention toward financial security. In doing so, they divert cognitive resources away from environmental goals. These effects are large relative to the baseline green adoption rate of 39 percent, underscoring how discomfort, cost salience, and stress weaken contributions to collective goods.

Our findings align with evidence that environmental pressures reduce cognitive performance and narrow attention. Heat impairs learning (Park et al. 2020), undermines decision quality (Heutel et al. 2021), and increases aggression and violence (Hsiang et al. 2013). Air pollution lowers test performance (Zhang et al. 2018), depresses workplace productivity (Chang et al. 2019), and raises crime rates (Bondy et al. 2020). Heat also increases rejection rates for immigration applications by U.S. judges (Heyes and Saberian 2019). Yet this literature focuses mainly on productivity, learning, and judgment under stress. We extend these insights to the domain of sustainability, showing that the same environmental pressures also reduce pro-social contributions to climate mitigation. Even when actions are low-cost and easily accessible, environmental stress diminishes households' willingness to engage in sustainable behavior.

Third, targeted policy interventions can effectively enhance sustainable choices in short-term by refocusing attention on environmental goals. Nationwide events such as Clean & Green Singapore increase green delivery uptake by 7 percentage points on the day of exposure, which is a 17 percent increase relative to baseline. This demonstrates the effectiveness of salience-based interventions or "green nudges" (Carlsson et al. 2021). Placebo tests show no anticipatory or lagged effects, indicating that campaigns operate through short-lived shifts in attention rather than persistent preference changes. Together, these results show that attention is both scarce and elastic: environmental stress depletes it, while policy salience can restore it in ways that materially affect sustainable behavior.

We also conduct a comprehensive set of robustness checks confirming that these effects are highly specific. Environmental shocks and campaigns leave order value, basket size, delivery fees, and platform pricing unchanged. The impact is confined to the environmental dimension of the decision, ruling out income effects, substitution between delivery options, or supply-side pricing responses. The evidence points instead to a reallocation of attention as the key channel through which salience shapes behavior.

To interpret these findings, we develop a simple behavioral inattention framework of green delivery choice. A central challenge in sustainable consumption is that the benefits of pro-environmental actions are diffuse, delayed, and non-monetary, while the costs are immediate and salient (Gabaix 2019; DellaVigna 2009). Our model formalizes the idea that households allocate scarce attention across these dimensions. Our model formalizes the idea that households fully attentive to the long-term and diffuse benefits of green delivery. Correspondingly, their green decisions are shaped by the allocation of scarce attentional resources, which maps directly to our empirical results:

Physical stressors such as heat and air pollution narrows this attention and create a tunneling effect (Mullainathan and Shafir 2013). This explains the sharp reductions in green delivery adoption we observe during adverse conditions. Electricity price-cap events operate through the same channel by heightening awareness of financial strain and shifting attention to immediate costs rather than environmental goals, even though the monetary price of green delivery itself does not change. In contrast, salience shocks redirects this attention. On one hand, sustainability campaigns increase the perceptual prominence of environmental benefits (Bordalo et al. 2013). This mechanism explains the immediate surge in adoption on event days. On the other hand, order characteristics such as more green delivery options in the choice menu, high value, etc. shift the focus to immediate costs. This mechanism is consistent with the findings that higher-value, bigger size, heavier orders are associated with lower green choices. The model also predicts, and our estimates confirm, that the effect of salience shocks is weaker under high stress because tunneling crowds out the cognitive capacity needed to process external prompts (Mani et al. 2013).

The behavioral inattention framework, therefore, provides a unifying explanation for both sets of results. Adverse conditions reduce contributions to collective goods by narrowing attention to the present, while salience interventions counteract this tendency by shifting attention back toward the future, but only when sufficient cognitive bandwidth is available.

Related Literature This paper contributes to several strands of research. First, we add to the literature on cognitive scarcity and decision-making. The foundational work by Mullainathan and Shafir (2013) and Shah et al. (2012) establishes that when individuals face stress, whether financial, physical, or psychological, their effective attentional capacity narrows, creating a 'tunneling' effect that focuses attention on immediate concerns at the expense of longer-term goals. This cognitive scarcity framework has been validated across diverse domains, including finance, education, and productivity. Recent experimental evidence has also shown how cognitive load affects specific types of decisions. Dean (2024) demonstrates that noise increases reduce productivity, with participants remaining unaware of this degradation. Deck and Jahedi (2015) provide consistent evidence that cognitive load increases both risk aversion and money-related impatience, while Dohmen et al. (2010) show that lower cognitive ability correlates with greater risk aversion and more pronounced impatience. The neural mechanisms underlying these effects have been traced by Huijsmans et al. (2019), who demonstrate that a scarcity mindset affects brain networks governing goal-directed decision making. Individuals may experience a self-control conflict between the temptation to act selfishly and the better judgment to act pro-socially (Martinsson et al. 2012; Wyss et al. 2022).

Second, we connect to research on environmental stress and economic performance. Temperature effects have been extensively documented: Dell et al. (2012) find that warming significantly depresses growth and industrial output in developing countries. Air pollution presents another well-established channel. Zivin and Neidell (2012) demonstrate that even moderate pollution significantly reduces farm worker productivity, while Chang et al. (2019) find similar effects in communication-intensive services, where higher pollution reduces completed calls and efficiency. These productivity effects extend to cognitive performance: Zhang et al. (2018) show that air pollution exposure lowers test performance, and Bondy et al. (2020) documents increased crime rates during polluted periods.

The physiological mechanisms underlying heat effects are well understood. Heat generated during activity must be dissipated to maintain body temperature and avoid heat stress (Kjellstrom et al. 2009). When body temperatures cannot be maintained at a given activity level, work intensity must be reduced. The efficiency of this thermoregulatory process depends primarily on ambient temperature but is also influenced by humidity and wind speed (Parsons 1993). Laboratory studies therefore, often employ wet-bulb temperature (WBT), which accounts for these combined factors (Lemke and Kjellstrom 2012). Recent evidence by Somanathan et al. (2021) confirms that hot days depress daily output and increase absenteeism in Indian manufacturing.

Third, we contribute to the literature on household sustainability choices. Research highlights heterogeneity in environmental preferences. This literature reveals substantial heterogeneity in how households respond to environmental information, incentives, and choice contexts. High-frequency feedback mechanisms demonstrate that real-time information makes consumers significantly more price-responsive to energy costs (Jessoe and Rapson 2014). Social comparison interventions provide compelling evidence that peer benchmarking induces economically meaningful energy conservation, with effects that decay over time but remain partially persistent even after direct mailings cease (Allcott and Rogers 2014).

The relative effectiveness of different intervention types has been examined through field experiments comparing moral suasion with monetary incentives. von Zahn et al. (2025) run a large-scale field experiment and find that notifying customers of the negative environmental impact of returns successfully reduced them by 2.6% without hurting sales. Ito et al. (2018) show that both approaches generate conservation, but through distinct behavioral dynamics and with pronounced heterogeneity across households, suggesting potential complementarity rather than simple substitution between policy tools. This heterogeneity extends to information processing mechanisms: structural demand studies reveal that eco-labels versus precise energy-bill information sort consumers into distinct behavioral types, highlighting fundamental differences in attention allocation and preference structures (Houde 2018).

In durable goods markets, household sustainability choices exhibit systematic patterns of incomplete optimization. Consumers fail to fully capitalize future fuel costs when purchasing vehicles and demonstrate heterogeneous valuations of fuel economy, creating important implications for the welfare and emissions impacts of environmental tax policies (Allcott and Wozny 2014; Grigolon et al. 2018). These patterns of bounded rationality extend to investment decisions: randomized and quasi-experimental evaluations of home energy retrofits consistently show that realized savings fall substantially short of engineering forecasts, highlighting implementation frictions and selection effects that vary systematically across household types (Fowlie et al. 2018). Households are only willing to pay a fraction of the net financial and environmental value generated by energy-efficient products, a gap largely driven by credit constraints rather than inattention to savings (Berkouwer and Dean 2022).

Building on these insights into preference heterogeneity and context-dependent choice, our platform setting provides a unique opportunity to isolate how same-day environmental prompts interact with price and availability constraints in real purchasing decisions. Unlike previous studies that examine long-term investments or monthly consumption patterns, we observe immediate behavioral responses to salience shocks, allowing us to estimate heterogeneous treatment effects across buyers and environmental contexts while controlling for stable preferences through individual fixed effects.

The paper proceeds as follows. Section 2 describes the background and data. Section 3 presents the empirical results. Section 4 interprets these results using a simple behavioral inattention framework. Section 5 discusses implications and future directions. Section 6 concludes.

2 Background and Data

2.1 Background

To isolate how salience and attention drive sustainable choices, we use a unique dataset of household purchases alongside exogenous sources of variation: local weather conditions and environmental events.

Our unique high-frequency administrative data comes from RedMart, a leading online grocery retailer in Singapore operating under Alibaba Group via Lazada. Similar with companies such as Amazon Fresh, RedMart offers scheduled deliveries of fresh produce, dairy, meat, and other household essentials through the Lazada app. RedMart was initially founded in 2011 to provide home delivery of groceries and household essentials. It was acquired by Lazada, one of Southeast Asia's largest e-commerce platform (owned by Alibaba Group) in 2016. In 2019, RedMart was fully integrated into the Lazada app.

The sustainable behavior we examine is linked to RedMart's strategy of encouraging users to choose "green delivery" options over standard ones: At checkout, customers will be prompted to select a delivery time slot (as shown in Figure 1) after choosing their delivery address. If a time slot allows multiple orders to be delivered together (i.e., 2 or more at once), choosing that slot over others helps reduce carbon emissions, making it a 'green delivery' option. RedMart highlights these slots with a 'Less CO_2' label, as seen on options like '2pm-4pm' and '3pm-5pm' in Figure 1. These green delivery slots offer no financial or other incentives beyond the environmental label itself.

[Insert Figure 1]

The delivery service pricing consists of two components: a slot fee and a shipping fee. The slot fee varies based on delivery urgency and flexibility—longer, less specific time windows incur lower fees. For example, a 6-hour slot (e.g., 8am-2pm) is free of charge, while a 2-hour slot (e.g., 1pm-3pm) incurs a fee of \$3.99. Express slots, defined as 2-hour windows available for same-day or next-morning delivery, carry an even higher surcharge. In contrast, the shipping fee is a flat rate of \$5.99, which is waived for orders exceeding \$60.

2.2 Administrative Data

We randomly sampled 100,000 delivery orders from RedMart, covering the period from March 2023 to March 2025. All data were anonymized by RedMart to ensure user privacy. Our analysis focuses on the 36,907 orders in the sample where customers were shown at least one green option.

Panel A of Table 1 presents summary statistics for this dataset, which captures information across three main dimensions for each order:

First, for each order, the dataset summarizes the delivery time slots availability presented to the customer at the time of selection. *avail entries* indicates the total number of delivery slots available. *eco entries* represents the number of green delivery slots—those labeled "Less CO2." *eco avail entries* denotes the number of green slots actually available to the user. *charged entries* captures the number of delivery slots that incur a slot fee (i.e., the fee is greater than zero). *charged avail entries* refers to the number of available slots among those that are charged.

We construct a new variable, *proportion*, defined as the share of green delivery slots in the menu at the time of choice (*eco avail entries* divided by *avail entries*). It is one of the key independent variables in our analysis, averaging 23.6% with substantial variation (SD=19.1%, range: 0.6%-100%). This variation is crucial for identification, as it reflects quasi-random fluctuations in delivery capacity that are plausibly orthogonal to individual environmental preferences. The typical customer faces approximately 17 total delivery slots, of which 2.2 are available green options.

Second, the dataset includes a summary of the order characteristics, including the expenditure, weight, and quantity. *expensive* is a dummy variable for high-value orders. *qty* represents the basket size in units, defined as the sum of the quantities of all individual items. *order weight* measures the total weight of the order. *shipping fee* and *slot fee* show the two parts of expenses paid for the delivery service of each order. In our sample, orders span a wide value range, with 56.9% classified as high-value. Basket sizes are substantial with correspondingly large weights, reflecting the nature of grocery delivery, where consumers consolidate household shopping into single orders.

Third, the dataset provides variables capturing the user's actual delivery choice in each order: *green* is a binary indicator of whether the selected time slot was a green delivery option, coded as one when the customer selects the low-emissions alternative. It is the key dependent variable in our analysis, providing a high-frequency measure of households' environmental-friendly behavior. It exhibits meaningful variation with 38.6% of orders selecting the environmentally-friendly option. *delivery postcode 2d* records the first two digits of the delivery postcode, providing coarse geographic information while maintaining privacy.

Overall, the summary statistics of this dataset shows that green choices are common rather than rare, and that *proportion* varies meaningfully within buyer and district over time. The distributions of *qty* and *order weight* are wide and right-skewed. Together these features support identification that relies on short-run variation within buyer, district, year by month, and day of week.

[Insert Table 1]

2.3 Meteorological Data

To measure local weather conditions, we employ several datesets, including Historical Daily Records Dataset, developed by Meteorological Service Singapore, and high-frequency data from Singapore's open data portal, developed by Singapore government. We also get daily air pollution data from Singapore's open data portal.

The first dataset compiles daily meteorological records from 22 stations across Singapore, starting in 1980. It includes key variables such as maximum, minimum, and mean temperature, wind speed, and rainfall, but most of them are only available after 2011.

The second dataset includes minute-by-minute air temperature and relative humidity readings at the weather-station level, starting in 2016. Weather data are aggregated to the district level using a nearest-station algorithm. We map stations to the nearest 28 districts, averaging the four closest stations for each district, and then linking each district to its corresponding postal sectors.

We also get the Historical Pollutant Standards Index dataset from the Singapore's open data portal, starting from 2023 to 2025. This dataset records daily historical pollutant standards index (PSI) for Singapore by region. It includes five regions across Singapore, east, west, north, south, and central. Besides, we also use electricity data from Energy Market Authority (EMA) in Singapore. For our analysis, we also match the region-level PSI data to the postal level. Both yield postal measures that align with our green delivery dataset.

Our analysis focuses on three key meteorological measures. The first is air pollution, measured using Singapore's Pollutant Standards Index (PSI). The PSI is the official composite indicator of air quality, published daily by the National Environment Agency. It aggregates concentrations of six major pollutants, including fine particulate matter ($PM_{2.5}$ and PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO), into a single index. Values below 50 are classified as 'good', 51 to 100 as 'moderate', 101 to 200 as 'unhealthy', and higher values as 'very unhealthy' or 'hazardous'. To link this measure to household choices, we match each postal sector in our delivery dataset to the corresponding district, as residents in different regions experience different levels of air pollution and may respond differently to their local air quality conditions. Since Singapore does not have official, standardized geographic boundaries for these five regions, we mapped them to postal code areas using a combination of NEA's regional classifications for PSI reporting, Urban Redevelopment Authority (URA) district definitions, and common geographical knowledge of Singapore's areas. In our dataset, each postal code is matched to one of the five PSI regions, and all postal codes within the same region are assigned the same PSI value for each calendar day between 2023 and 2025. This approach ensures that each individual's pollution exposure reflects the air quality in their specific geographic area, allowing us to capture potential regional differences in how pollution affects consumer behavior.

The second is wet-bulb temperature (Twb), which captures the stress feeling of heat and humidity. To calculate this temperature, we first get the 5-minute level temperature (T, in °C) and relative humidity (RH, in %) by station level. Then, to match the postal level data in our main dataset, we use the nearest four stations and get district-level data by averaging the four values of temperature and humidity. Then we use the following approximation (Stull 2011).

$$\begin{aligned} T_w \approx T \cdot \arctan\Big(0.151977\sqrt{RH + 8.313659}\Big) \\ + \arctan(T + RH) - \arctan(RH - 1.676331) \\ + 0.00391838\, RH^{3/2} \cdot \arctan(0.023101\, RH) - 4.686035. \end{aligned} \tag{1}$$

Extreme weather will lead to extreme electricity prices. Thus, to illustrate extreme weather days, we use the temporary price cap (TPC) as a binary indicator, defined as 1 if the temporary price cap is triggered, otherwise 0. It was introduced by Singapore's Energy Market Authority (EMA) on 1 July 2023 as a short-term safeguard for consumers against unusually high electricity prices in the wholesale market. The idea is to set a ceiling (cap) on the Uniform Singapore Energy Price when extreme spikes occur. The cap kicks in only when wholesale market prices exceed a specified threshold. Prices above the cap are absorbed and settled by the Market Support Services or balancing arrangements, rather than passed directly to consumers.

Table 1 Panel B summarizes the meteorological, air-quality, cost, and event variables. The temporary price-cap indicator (TPC) equals one when the cap is triggered; its mean is 0.058 and its standard deviation is 0.234, with a range of 0 to 1. During our sample period, we had 1,653 observations that triggered TPC. District-day wet-bulb temperature (Twb) averages 25.069 degrees Celsius with a standard deviation of 0.751, ranging from 22.01 degrees Celsius to 27.54 degrees Celsius. Air quality, measured by the Pollutant Standards Index (PSI), averages 45.424 with a standard deviation of 11.972, and ranges from 14.292 to 108.375. The same-day green-event indicator (*HasEvent*) has a mean of 0.086 and a standard deviation of 0.280, with values from 0 to 1.

2.4 Green Events Data

In addition to weather shocks, we compile a dataset of environmental awareness events in Singapore between 2023 and 2025. We systematically hand-collected these events from official announcements by the National Environment Agency (NEA), the Ministry of Sustainability and the Environment (MSE), and affiliated public campaigns (e.g., *Clean & Green Singapore Day, Go Green SG, World Cleanup Day*). Each event is coded with its start and end dates, scope, and category. It includes both weather-related disruptions (such as prolonged dry spells or oil-spill cleanups) and publicity-driven environmental campaigns (such as recycling drives and sustainability awareness initiatives).

To integrate these events into our empirical analysis, we expand each event into a daily panel, matching the event period to the transaction-level dataset by calendar date. We then construct an indicator variable, *HasEvent*, equal to one on days when at least one green event took place, and zero otherwise. This construction allows us to isolate the incremental effect of policy-driven awareness campaigns. Table A1 in the Online Appendix presents a listing of the events.

This dataset of green events represents a novel effort to link Singapore's environmental publicity campaigns with high-frequency consumer choice data. Prior work has often relied on survey-based measures of environmental attitudes or cross-sectional exposure to policy initiatives. By contrast, our daily coding of campaigns and disruptions allows us to study short-run variation in exposure within a quasi-experimental framework. Since most campaigns are nationwide in scope and receive broad media coverage, their timing is plausibly exogenous to individual transaction-level choices. Their short duration and clear documentation provide useful within-period contrasts to evaluate whether consumer choices respond to government-led environmental cues.

3 Empirical Results

We now present our main findings. Section 3.1.1 tests how air pollution affects consumer green choice. Section 3.1.2 investigates whether wet-bulb temperature influences green-consuming behavior. Section 3.1.3 presents how electricity prices influence green-consuming behavior. Section 3.2 explores whether consumers adjust consumption choice in response to green events. Section 3.3 examines the internal drivers of green delivery. Our large sample size (approximately 11,000 observations for most specifications) provides sufficient power to detect economically meaningful effects. Standard errors are appropriately clustered at the individual level to account for repeated observations, and the comprehensive fixed effects structure ensures that our estimates reflect true behavioral responses rather than selection or confounding factors.

3.1 Environmental Shocks and Green Delivery

Having established the baseline determinants of green choice, we now test our central hypothesis: environmental stressors systematically reduce sustainable behavior by narrowing attention to immediate comfort and cost concerns. We examine three distinct measures of physical and cognitive strain that theory suggests should crowd out environmental considerations: air pollution (physical discomfort), heat-humidity (physiological strain), and electricity price shocks (financial salience).

3.1.1 Air Pollution

Air pollution provides a direct test of how physical discomfort influences sustainable behavior. Poor air quality creates immediate physiological stress and has been shown to impair cognitive function, which can reduce the mental bandwidth available for environmental considerations. To examine whether pollution systematically shifts choices away from green delivery, we exploit the daily variation in Singapore's Pollutant Standards Index (PSI).

As mentioned earlier, the PSI is the official composite indicator of ambient air quality, incorporating multiple pollutants into a single measure published daily by the National Environment Agency. We use district-day variation in PSI as a plausibly exogenous proxy for exposure to air pollution and the associated cognitive and physiological strain it imposes on households. Formally, we test the impact of air pollution using the following specification:

$$\begin{aligned} Green_{i,t} = \alpha + \beta_1\, PSI_{d,t} + \beta_2\, Proportion_{i,t} + \beta_3\, OrderChar_{i,t} \\ + \gamma_i + \delta_d + \theta_t + \eta_t + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

Here, the dependent variable $\text{Green}_{i,t}$ equals one if order i on date t was delivered via the green option. The key regressor $\text{PSI}_{d,t}$ denotes the Pollutant Standards Index in district d on date t. $\text{Proportion}_{i,t}$ is the share of green slots in the delivery menu. The specification controls for $\text{OrderChar}_{i,t}$, which includes $\text{Expensive}_{i,t}$, $\text{Qty}_{i,t}$, and $\text{Orderweight}_{i,t}$ (total order weight).

To control for unobserved heterogeneity, the model includes individual fixed effects (γ_i), postal sector fixed effects (δ_d), year-month fixed effects (θ_t), and day-of-week fixed effects (η_t). Standard errors are clustered at the individual level.

Table 2 demonstrates how air quality systematically affects green delivery choice. The pollution measure (PSI) has a consistent negative effect across all specifications, with a coefficient of -0.0012–0.0015 (statistically significant at 5% level).

[Insert Table 2]

To put this effect in perspective, consider extreme pollution days. Singapore occasionally experiences PSI levels above 80 during regional haze episodes from Indonesian forest fires. Our estimates suggest that such days would reduce green delivery adoption by approximately 7.15 percentage points compared to clean air days (PSI around 25). This represents a meaningful behavioral response to environmental stress, particularly given that these extreme events can persist for weeks during dry seasons. The negative pollution effect is consistent with cognitive scarcity theories. Poor air quality creates physical discomfort and has been documented to impair cognitive function (Chen et al. 2024), reduce workplace productivity, and increase irritability. Under these conditions, customers likely focus on immediate relief and convenience, reducing their willingness to accept the scheduling constraints associated with green delivery. The effect operates independently of order characteristics, as evidenced by the stability of the coefficient when controls are added in Columns 2 and 3. Besides, the *Proportion* coefficient remains large and statistically significant at 1% level (0.4468-0.4732) even when pollution is controlled for. This is unsurprising, and highlight that menu structure continues to influence choice even under environmental stress, though the baseline propensity for green choice is reduced.

3.1.2 Wet-Bulb Temperature

Next, we examine the role of heat and humidity, which generate physiological stress that can impair cognitive performance and redirect attention toward immediate comfort concerns. Wet-bulb temperature provides a particularly relevant metric because it captures the combined effect of heat and humidity on human thermal stress. Unlike simple air temperature, wet-bulb temperature reflects the body's capacity to cool through perspiration and thus serves as a direct indicator of physical discomfort. We use this measure to test whether heat-humidity stress systematically reduces the weight households place on environmental considerations in daily consumption choices. Formally, we estimate:

$$\begin{aligned} Green_{i,t} = \alpha + \beta_1\, \mathrm{Twb}_{d,t} + \beta_2\, \mathrm{Proportion}_{i,t} + \beta_3\, \mathrm{OrderChar}_{i,t} \\ + \gamma_i + \delta_d + \theta_t + \eta_t + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

In this specification, the main explanatory variable $\mathrm{Twb}_{d,t}$ measures district-day wet-bulb temperature, a proxy for heat-humidity stress that combines air temperature and relative humidity using the Stull (2011) approximation. A negative β_1 implies that higher heat stress reduces the probability of choosing green delivery. $\mathrm{Proportion}_{i,t}$ measures green slot availability, and $\mathrm{OrderChar}_{i,t}$ includes order characteristics. All other controls, fixed effects, and clustering follow Equation (2).

Table 3 examines the effects of wet-bulb temperature, which captures the combined stress from heat and humidity. The results strongly support our attention-based framework. The coefficient on Twb in Columns 1-3 is consistently negative and significant at 1% level across specifications (-0.041 to -0.0434), indicating that heat-humidity stress substantially reduces green delivery choice. For extreme weather, Singapore's wet-bulb temperatures range from 22°C to 27.5°C in our sample, spanning from comfortable conditions to physiologically stressful levels. Our estimates imply that moving from cool, dry conditions (22°C) to hot, humid conditions (27.5°C) would reduce green delivery adoption by approximately 20.02 percentage points, which is a massive behavioral response. Such extreme conditions occasionally occur during heat waves and are projected to become more frequent under climate change, suggesting that rising temperatures could significantly undermine sustainable behavior.

[Insert Table 3]

Wet-bulb temperature is particularly relevant because it measures the theoretical limit of evaporative cooling. When wet-bulb temperatures exceed certain thresholds, the human body cannot effectively dissipate heat through sweating, creating immediate physiological stress. This forces attention toward thermal comfort and away from other considerations, including environmental goals. This mechanism is distinct from general temperature effects and directly relates to human comfort and cognitive capacity under heat stress.

Column 4 tests whether heat stress alters the effectiveness of menu design by including an interaction between Twb and *Proportion*. The interaction coefficient is small and insignificant (-0.0181), suggesting that menu prominence effects remain stable across temperature conditions. This finding is encouraging for policy design, as it indicates that interface interventions maintain their effectiveness even under climate stress, though the baseline probability of choosing green options declines.

3.1.3 Electricity Prices

Finally, financial stress provides a third channel through which environmental conditions can crowd out sustainable behavior. When energy costs become salient, consumers may shift attention toward immediate financial concerns, reducing their willingness to accept potential inconveniences associated with green delivery. Singapore's temporary price cap (TPC) mechanism provides a natural experiment: when wholesale electricity prices spike unexpectedly, the TPC is triggered, creating heightened awareness of energy costs across the population. We test whether these cost salience shocks systematically reduce environmental consideration, even when green delivery prices remain unchanged.

$$\begin{aligned} Green_{i,t} = \alpha &+ \beta_1\, \mathrm{TPC}_t + \beta_2\, \mathrm{Proportion}_{i,t} + \beta_3\, \mathrm{OrderChar}_{i,t} \\ &+ \gamma_i + \delta_d + \theta_t + \eta_t + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

The binary regressor TPC_t equals one on dates when the temporary price cap (TPC) is triggered in Singapore's wholesale electricity market. This indicator captures budget pressure and the salience of cost concerns. A negative β_1 suggests that cost stress shifts attention away from environmental attributes. $\mathrm{Proportion}_{i,t}$ measures green slot availability, and $\mathrm{OrderChar}_{i,t}$ includes order characteristics. Controls, fixed effects, and clustering are as in Equation (2).

Table 4 analyzes how budget pressure affects green delivery choice using an indicator for days when a temporary price cap on electricity is applied. The intuition is that higher salience of costs increases loss aversion with respect to potential delays or uncertainty, which reduces the appeal of the green option even if the posted price for green is unchanged. Column 1 shows a negative and significant association between TPC and green. Columns 2-3 add $\text{Proportion}_{i,t}$ and the order covariates.

[Insert Table 4]

The *TPC* coefficient is consistently negative and significant across both specifications (-0.0682 in Column 1, -0.0711 in Column 2, 0.0701 in Column 3, all significant at 5% level), showing that price cap events reduce green delivery adoption by approximately 6.8-7.1 percentage points. Given that TPC events occur on only 5.8% of days in our sample, this represents a large behavioral response to cost salience shocks, which is substantially larger than typical day-to-day variations in environmental conditions. The economic interpretation is that heightened awareness of energy costs shifts attention toward immediate financial considerations, crowding out environmental goals. The mechanism operates through increased loss aversion: when cost concerns are salient, consumers become more risk-averse about potential delays or uncertainty associated with green delivery, even though green delivery pricing itself remains unchanged during TPC events. This psychological salience effect is consistent with attention-based theories of decision-making, where the mere awareness of financial stress can alter choice patterns.

Column 3 demonstrates that the TPC effect remains stable when controlling for menu structure and order characteristics. The *Proportion* coefficient (0.4267, statistically significant at 1% level) shows that menu prominence continues to drive green adoption even during periods of financial stress, though the baseline propensity is reduced. The negative coefficients on *expensive*(-0.0733) and *qty* (-0.0030) are consistent with our earlier findings about how financial stakes and order complexity reduce sustainable choice.

The TPC effect (-6.8 to -7.1 percentage points) is substantially larger than the pollution effect (-0.1 percentage point per point) and comparable to moderate heat stress effects (-4.1 to -4.3 percentage points per point). This suggests that financial salience may be particularly potent in crowding out sustainable behavior, consistent with literature showing strong effects of budget constraints on cognitive capacity. The immediate and tangible nature of cost concerns appears to dominate more abstract environmental considerations.

3.2 Environmental Events and Green Delivery

Having documented how environmental stressors reduce sustainable behavior, we now test whether targeted interventions can counteract these effects by redirecting attention toward environmental goals. Environmental awareness campaigns provide a natural experiment to test attention-based theories: if green choices depend on the salience of environmental considerations, then promotional events that highlight sustainability should increase green delivery adoption, particularly on the day of exposure.

Singapore's environmental campaigns offer an ideal setting for this analysis. The National Environment Agency and Ministry of Sustainability and the Environment regularly organize nationwide environmental awareness events that receive broad media coverage. These campaigns are typically announced in advance and focus public attention on sustainability themes through various channels including social media, traditional media, and public installations. If attention mechanisms drive sustainable behavior, we expect these events to create sharp, temporary increases in green delivery choice.

$$\begin{aligned} Green_{i,t} = \alpha &+ \beta_1 \, \mathrm{HasEvent}_t + \beta_2 \, \mathrm{Proportion}_{i,t} + \beta_3 \, \mathrm{OrderChar}_{i,t} \\ &+ \gamma_i + \delta_d + \theta_t + \eta_t + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

We evaluate this mechanism using a hand-coded daily indicator for environmental events ($\mathrm{HasEvent}_t$) and the same order-level specification with controls and fixed effects. In additional placebo tests (see Appendix Table A2 and Table A3), we include ± 7 and ± 14 day leads and lags to assess timing specificity. The baseline specification is shown in Equation (5).

Here, $\mathrm{HasEvent}_t$ is a dummy variable equal to one on dates when at least one environmental awareness campaign is active (see Appendix Table A1 for the complete listing). A positive β_1 indicates that salience shocks increase consumers' willingness to choose the green option. $\mathrm{Proportion}_{i,t}$ measures green slot availability, and $\mathrm{OrderChar}_{i,t}$ includes order characteristics. Controls, fixed effects, and clustering are as in Equation (2). The timing specificity of this effect provides a key test distinguishing attention-based from preference-based mechanisms.

Table 5 measures the same-day impact of a salient green prompt and demonstrates that targeted interventions can counteract the negative effects of environmental stress by redirecting attention toward sustainability goals. The HasEvent coefficient shows a strong positive effect (0.0369-0.0700, statistically significant), indicating that green promotional events increase same-day green delivery adoption by approximately 3.6-7 percentage points. This demonstrates the power of salience interventions.

[Insert Table 5]

The events in our analysis (detailed in Appendix Table A1) include Earth Day promotions, World Environment Day campaigns, Clean & Green Singapore initiatives, and various sustainability awareness drives. These events typically feature prominent green messaging across multiple media channels, environmental education content, community activities, and sometimes small promotional incentives. The large effect size suggests that even modest interventions can significantly shift behavior when they successfully redirect attention toward environmental goals.

Importantly, the event effect operates independently of menu structure, as evidenced by the relatively stable $\text{Proportion}_{i,t}$ coefficient across Columns 2-6 (ranging from 0.426 to 0.510). This independence suggests that promotional events and interface design work through different channels. Events increase the salience of environmental goals at the moment of choice, while menu structure affects the probability that green options are noticed and considered within the choice set.

However, Column 6 reveals an important interaction: the coefficient on *HasEvent* × *proportion* is positive and statistically significant at the 5% level (0.218), while the standalone *HasEvent* effect becomes insignificant (0.011). This pattern indicates that promotional events are most effective when the menu already contains a substantial proportion of green options. The complementarity between event salience and menu structure suggests that combining both interventions yields more than additive effects. Events amplify the impact of green-friendly menu designs rather than simply adding to them.

The progression from Column 5 to Column 6 is particularly revealing. Without the interaction term (Column 5), *HasEvent* shows a marginally significant effect at the 10% level (0.070). Once we allow for heterogeneous treatment effects through the interaction (Column 6), we see that the event impact is concentrated among orders where green options are more prevalent in the menu. This finding has practical implications: promotional campaigns may be most cost-effective when coordinated with merchants who already offer diverse green delivery options.

3.2.1 Interaction of Environmental Stress and Salience

We next examine whether environmental stress moderates the effectiveness of promotional events. Table 6 presents evidence on how two distinct stressors, heat-humidity (measured by wet-bulb temperature) and air pollution (measured by PSI), interact with same-day green delivery promotional events.

[Insert Table 6]

Heat-Humidity Stress Panel A examines wet-bulb temperature (T_{wb}), which captures the combined physiological stress from heat and humidity. Column 1 shows the baseline specification with only T_{wb} and *HasEvent* as regressors. The *HasEvent* coefficient is positive and statistically significant at the 1% level (0.0579), confirming that promotional events increase green delivery adoption. However, T_{wb} itself shows no significant direct effect (-0.0005).

Column 2 introduces the interaction term *HasEvent* $\times$ T_{wb} without control variables. The interaction coefficient is negative and statistically significant at the 1% level (-0.0420), indicating that the effectiveness of promotional events diminishes under heat-humidity stress.

Columns 3-4 replicate this analysis with the full set of controls and fixed effects. Column 3 includes *proportion*, *expensive*, *qty*, *order weight*, *slot fee*, and individual, district, day-of-week, and year-month fixed effects. In this specification, T_{wb} becomes negative and statistically significant at the 1% level (-0.0400), suggesting that heat-humidity stress directly reduces green delivery choice once we account for individual heterogeneity and temporal patterns. The *HasEvent* effect remains positive but is now only marginally significant at the 10% level (0.0642).

Column 4 adds the interaction term to the full specification. The interaction coefficient is negative and statistically significant at the 1% level (-0.0890), and substantially larger in magnitude than in Column 2. This means that a one-unit increase in wet-bulb temperature reduces the promotional event's effectiveness by 0.089 percentage points. Given that the average event effect (at mean T_{wb}) is approximately 0.06-0.07 percentage points, this interaction effect is economically meaningful. At sufficiently high temperatures, the promotional boost could be entirely offset.

Air Pollution Stress Panel B repeats this analysis using the Pollutant Standards Index (PSI) as the environmental stressor. The pattern largely mirrors Panel A. In the baseline specification (Column 1), PSI shows a small positive coefficient (0.0007), statistically significant at the 1% level, which appears counterintuitive. However, this positive association likely reflects omitted variable bias. Pollution may correlate with urban density or economic activity, which themselves correlate with green preferences.

Column 2 introduces the interaction HasEvent $\times$ PSI. The interaction is negative and statistically significant at the 1% level (-0.0056), confirming that air pollution also dampens the effectiveness of promotional events. The standalone HasEvent coefficient (0.3242) again represents the event effect at zero pollution.

Columns 3-4 include the full controls and fixed effects. In Column 3, the PSI coefficient becomes negative and statistically significant at the 5% level (-0.0012), consistent with the hypothesis that pollution imposes cognitive costs that reduce pro-environmental behavior. The sign reversal from Column 1 to Column 3 underscores the importance of controlling for individual and spatiotemporal heterogeneity.

Column 4 shows that the interaction HasEvent $\times$ PSI remains negative and statistically significant at the 1% level (-0.0059) even with all controls. This coefficient implies that a 10-unit increase in PSI (roughly the difference between 'Good' and 'Moderate' air quality) reduces the event's effectiveness by 0.059 percentage points.

Interpretation and Mechanisms The consistent negative interaction effects across both stressors suggest a common underlying mechanism: environmental stress constrains cognitive resources available for processing salient information. When individuals are under physiological strain—whether from heat-humidity or air pollution—they appear less responsive to attention-directing interventions like promotional events. This is consistent with the dual-process framework, where environmental stressors deplete System 2 cognitive capacity, making individuals less able to engage with deliberative prompts.

Importantly, these interaction effects differ sharply from the null interaction between T_{wb} (or PSI) and menu proportion documented in Table 3. Menu structure operates through a more passive, System 1 mechanism: green options that are already prominent in the choice set are noticed and selected even under stress. In contrast, promotional events require active processing of salient information, which is precisely what environmental stress disrupts.

The magnitude of the interaction effects has practical implications for the timing and targeting of promotional campaigns. Our estimates suggest that green delivery campaigns would be most cost-effective when scheduled during periods of moderate temperatures and good air quality. During heat waves or pollution episodes, the same campaign expenditure would yield substantially lower returns. This finding highlights a novel externality of environmental degradation: it not only directly harms welfare but also undermines the effectiveness of policies designed to mitigate environmental problems.

Taken together, the results reveal a consistent pattern across interventions and stressors. Air pollution, heat-humidity, and electricity price shocks all reduce green delivery choice, while promotional events increase it—but the effectiveness of promotional events is itself conditional on environmental conditions. The interaction between salience and stress suggests that attention-directing interventions require not only a supportive choice architecture (as shown in Table 5) but also favorable external conditions to achieve their intended effects.

3.3 Drivers of Green Delivery

We begin by examining how internal drivers affect consumer decisions. Specifically, we estimate the effect of menu design and order characteristics on green delivery using the following transaction-level regression:

$$\begin{aligned} Green_{i,t} = \alpha + \beta_1\, Proportion_{i,t} + \beta_2\, Z_{i,t} \\ + \beta_3\big(Proportion_{i,t} \times Z_{i,t}\big) + \gamma_i + \delta_d + \theta_t + \eta_t + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

Here, the dependent variable $\text{Green}_{i,t}$ is an indicator equal to one if order i on day t selects the green delivery option. The key variable $\text{Proportion}_{i,t}$ measures the share of green slots available. $Z_{i,t}$ is a generic order characteristic, which in different columns of Table 7 is defined alternatively as $\text{Expensive}_{i,t}$ (high-value order dummy), $\text{Qty}_{i,t}$ (number of items), $\text{Order\_weight}_{i,t}$ (total order weight), or $\text{Slot\_fee}_{i,t}$. The interaction term $\text{Proportion}_{i,t} \times Z_{i,t}$ tests whether the marginal effect of menu design differs across order types. To control for unobserved heterogeneity, the model includes individual fixed effects (γ_i), postal sector fixed effects (δ_d), year-month fixed effects (θ_t), and day-of-week fixed effects (η_t). Standard errors are clustered at the individual level.

Table 7 examines the pass-through from menu design to green delivery choice, with particular attention to how order characteristics moderate this relationship. Columns 1-4 present baseline specifications without individual fixed effects, while Columns 5-8 include the full set of individual, district, day-of-week, and year-month fixed effects.

[Insert Table 7]

The most striking finding is the consistently strong positive effect of $\text{Proportion}_{i,t}$, the share of green delivery slots available in the menu. Across all eight specifications, the coefficient on $\text{Proportion}_{i,t}$ ranges from 0.459 to 0.599, all statistically significant at the 1% level. This implies that a 10 percentage point increase in green slot availability raises the probability of choosing green delivery by approximately 4.6-6.0 percentage points. The stability of this coefficient across different samples (full sample in Columns 1-4 with 36,907-36,888 observations versus fixed-effects sample in Columns 5-8 with 10,981-10,985 observations) and across varying control sets provides strong evidence for the robustness of menu structure effects.

This large menu effect supports our attention-based framework. When green options are more prominent in the choice set, they are more likely to be noticed and considered, leading to higher adoption rates. The magnitude suggests that simple changes to interface design can have meaningful impacts on sustainable behavior, a finding with important implications for platform design and policy interventions.

Order Value Heterogeneity. Column 1 examines how order value affects green delivery choice by including $\text{Expensive}_{i,t}$ (an indicator for orders $\geq$ S\$100) and its interaction with $\text{Proportion}_{i,t}$. The negative coefficient on $\text{Expensive}_{i,t}$ (-0.118, statistically significant at the 1% level) reveals a striking pattern: customers placing higher-value orders are 11.8 percentage points less likely to choose green delivery compared to those with smaller orders. This counterintuitive finding suggests that when customers make substantial purchases, they prioritize reliability and control over environmental considerations. High-value orders may increase the stakes associated with delivery timing, making customers more risk-averse about potential delays or scheduling constraints that could accompany green delivery options.

This pattern contrasts with typical assumptions that higher-income or higher-spending consumers are more willing to pay for environmental attributes. Instead, it appears that when significant money is at stake, immediate convenience concerns dominate sustainability goals, consistent with our attention-based framework, where financial salience crowds out environmental considerations.

The interaction term $\text{Expensive}_{i,t} \times \text{Proportion}_{i,t}$ is positive and statistically significant at the 1% level (0.0863) in the baseline specification (Column 1), suggesting that the menu prominence effect is actually stronger for high-value orders. A 10 percentage point increase in green proportion raises green choice by an additional 0.86 percentage points for expensive orders compared to cheaper ones. However, this interaction becomes small and insignificant (-0.0021) once we include individual fixed effects in Column 5. This suggests that the cross-sectional interaction in Column 1 may reflect customer heterogeneity rather than a true moderating effect: customers who place expensive orders may systematically differ in their responsiveness to menu design, but within-individual variation shows no such differential response.

Basket Complexity and Attention Allocation. Columns 2 and 6 reveal important insights about how order complexity affects green choice. The negative coefficient on $\text{Qty}_{i,t}$ is statistically significant at the 1% level in both specifications (-0.0037 in Column 2; -0.0024 in Column 6), showing that each additional item in the basket reduces green delivery probability by 0.24-0.37 percentage points. For a one-standard-deviation increase in quantity (approximately 15.74 items), this translates to a 3.8–5.8 percentage point reduction in green choice.

The interaction between $\text{Qty}_{i,t}$ and $\text{Proportion}_{i,t}$ tells a more interesting story. In the baseline specification (Column 2), the interaction is small and insignificant (0.0013), suggesting that menu prominence effects operate similarly regardless of basket size. However, once we control for individual fixed effects (Column 6), the interaction becomes negative and statistically significant at the 1% level (-0.0053). This means that within the same individual, the attention-directing effect of menu structure becomes less effective as baskets grow larger.

The economic interpretation is clear: when customers must evaluate many items, cognitive resources are taxed, reducing the attention available for secondary attributes like environmental impact. Each additional item shifts focus toward reliability and timing concerns. This finding directly supports cognitive scarcity theories and highlights how everyday complexity can undermine sustainable behavior. The differential results between Columns 2 and 6 also underscore the importance of within-individual identification: customer heterogeneity masks important interaction effects that only emerge when we compare the same person across different order sizes.

Order Weight Columns 3 and 7 examine how order weight affects green delivery choice. The negative coefficient on $\text{Order\_weight}_{i,t}$ is statistically significant at the 1% level in the baseline specification (-0.474, Column 3) and at the 5% level with individual fixed effects (-1.133, Column 7). This pattern indicates that heavier orders reduce green delivery choice, consistent with customers prioritizing reliability and speed for logistically complex deliveries. A 1 kg increase in order weight reduces green choice probability by 0.47-1.13 percentage points, depending on specification.

The interaction between $\text{Order\_weight}_{i,t}$ and $\text{Proportion}_{i,t}$ is positive but insignificant in Column 3 (0.261) and becomes negative and insignificant in Column 7 (-1.997). The large standard errors (0.541 in Column 3; 1.550 in Column 7) suggest substantial noise in this interaction, possibly because order weight varies considerably across different types of products and merchants. Despite this interaction uncertainty, the main effect of $\text{Proportion}_{i,t}$ remains large and highly significant (0.588 in Column 3; 0.531 in Column 7), suggesting that menu prominence effects persist even when fulfillment concerns are salient.

Delivery Slot Fees and Price Sensitivity. Columns 4 and 8 investigate how delivery slot fees moderate green choice. The negative main effect of $\text{Slot\_fee}_{i,t}$ (-0.0153 in Column 4; -0.0214 in Column 8, both significant at 1%) indicates that higher delivery fees reduce green adoption. Each S$1 increase in slot fee reduces green choice probability by 1.5–2.1 percentage points. This suggests that even modest price differences can deter sustainable choices, consistent with standard price elasticity.

More interesting is the negative interaction $\text{Proportion}_{i,t} \times \text{Slot\_fee}_{i,t}$, which is statistically significant at the 1% level in both specifications (-0.106 in Column 4; -0.076 in Column 8). This negative interaction indicates that the menu prominence effect weakens as delivery fees increase. When green delivery becomes more expensive, customers pay more attention to price comparisons and less attention to menu structure cues. This finding suggests a hierarchy of decision factors: price considerations can override the subtle nudges from interface design, especially when financial stakes become salient.

The economic interpretation aligns with our attention framework: when delivery fees are high, the monetary cost captures more cognitive attention, reducing the effectiveness of menu-based nudges. This has important policy implications. Pricing interventions and choice architecture work through different channels, and combining both may not yield additive effects if higher prices crowd out attention to menu design.

Robustness and Identification. The stability of the $\text{Proportion}_{i,t}$ coefficient across specifications (0.459–0.599) provides confidence in our identification strategy. The comprehensive fixed-effects structure in Columns 5–8 (individual, district, year-month, and day-of-week) ensures that our estimates reflect short-run variation in menu structure rather than systematic differences across customers, locations, or time periods. The R-squared jumps from approximately 0.054–0.067 in Columns 1–4 to 0.526–0.529 in Columns 5–8, indicating that individual heterogeneity accounts for the majority of explained variation in green delivery choice. However, the within-individual variation captured by menu structure and order characteristics remains economically and statistically significant, validating our focus on situational factors rather than fixed preferences.

4 Behavioral Framework

To explain the observed patterns, we propose a simple behavioral inattention framework of green delivery choice. A core challenge in promoting sustainable consumption is that the benefits of pro-environmental actions are often diffuse, delayed, and non-monetary, while their costs are immediate and salient. This creates a wedge between the objectively optimal choice for societal welfare and the subjectively perceived choice for a cognitively constrained individual. We draw upon the burgeoning literature on behavioral inattention (Gabaix 2019) to propose that a household's decision to opt for green delivery is fundamentally governed by the allocation of scarce cognitive resources, or attention, toward future environmental benefits.

This framework conceptualizes the choice of green delivery as an intertemporal trade-off, where attention modulates the weight placed on future utility. We formalize this intuition using a parsimonious model that unifies two key drivers of attention: cognitive scarcity induced by physical stress, which narrows attention, and salience shocks from green events, which redirect attention toward future environmental consequences.

4.1 A Simple Model of Inattentive Intertemporal Choice

Consider a household making a discrete choice $a \in \{G, N\}$ between Green delivery (G) and Non-green (standard) delivery (N). A fully rational agent derives utility from two dimensions: the immediate convenience or cost of delivery, and the future environmental impact. The utility of option a is given by:

$$U(a) = u_0(a) + \delta\, u_1(a), \tag{7}$$

where $u_0(a)$ is the immediate utility, $u_1(a)$ is the utility from the future environmental consequence, and $\delta \in (0, 1)$ is the standard discount factor.

The core trade-off is characterized by two key assumptions. First, the green option entails an immediate cost, such that $u_0(G) < u_0(N) \leq 0$, as it typically requires accepting less convenient delivery slots. Second, it provides a future environmental benefit, such that $u_1(G) > u_1(N) \geq 0$.

Following Gabaix (2019), we posit that individuals do not fully attend to the future environmental component. This yields a subjectively perceived utility:

$$U_a^s = u_0(a) + m\delta u_1(a), \tag{8}$$

where $m \in [0, 1]$ is the *attention weight* on the future utility. When $m = 1$, the household is fully attentive and behaves according to the standard rational model. In contrast, when $m < 1$, the household underweights the future environmental impact, exhibiting a form of hyperbolic discounting (Laibson 1997) but with a clear cognitive foundation.

The household chooses Green delivery if and only if $U^s(G) > U^s(N)$. Substituting the utilities, this condition becomes

$$[u_0(G) - u_0(N)] + m\delta\,[u_1(G) - u_1(N)] > 0. \tag{9}$$

Given that $u_0(G) - u_0(N) < 0$ (immediate cost) and $u_1(G) - u_1(N) > 0$ (future benefit), the inequality is more likely to hold when the attention parameter m is higher. Thus, the probability of choosing green delivery, $P(G)$, is an increasing function of m:

$$P(G) = \Phi(m). \tag{10}$$

For simplicity, we apply a logit choice model, so

$$\Phi(m) = \frac{1}{1 + \exp([u_0(N) - u_0(G)] - m\delta\,[(u_1(G) - u_1(N)])}. \tag{11}$$

In our empirical context, the choice of green delivery is not an extreme event; the baseline probability $P(G)$ is around 40%. Therefore, for the range of m we consider,

$$\frac{\partial^2 \Phi}{\partial m^2} \geq 0, \tag{12}$$

is a reasonable assumption. This implies that the marginal effect of attention on green choice is non-decreasing: when attention is low, initial increases may have a small effect, but as attention rises, the marginal effect may strengthen.

4.2 Cognitive Scarcity and Salience Shocks

The central premise of our framework is that external factors influence the choice $P(G)$ primarily through their impact on attention m. Let $P(G) = \Phi(m)$. We model attention as a function of physical stress S (e.g., heat, pollution) and green events E (e.g., World Cleanup Day), i.e.,

$$m = m(S, E).$$

Cognitive Scarcity. An increase in physical stress S depletes mental bandwidth. According to the theory of cognitive scarcity, this depletion triggers a tunneling effect (Mullainathan and Shafir 2013): attention narrows automatically and compulsively onto the immediate pressing need—in this case, alleviating discomfort or managing financial strain—and away from future-oriented goals like environmental protection. This implies the marginal effect of stress on attention is negative:

$$\frac{\partial m}{\partial S} < 0. \tag{13}$$

Salience Shock. While cognitive scarcity narrows attention, external cues can actively redirect it. Green events E such as World Cleanup Day, function as salience shocks that increase the perceptual prominence of the environmental attribute (Bordalo et al. 2013). In standard choice contexts, the future environmental benefit of a decision is often a less immediate and less salient attribute compared to cost or convenience. These events disrupt this default by making the environmental consequence more mentally accessible, thereby drawing a larger share of an individual's limited attention toward the future utility of the decision (Gabaix 2014, 2019). This implies the marginal effect of an event on attention is positive:

$$\frac{\partial m}{\partial E} > 0. \tag{14}$$

Attenuated Salience Effect under Scarcity. We further propose that cognitive scarcity not only directs attention away from future goals but also impairs the cognitive capacity to process new informational cues. The cognitive burden of coping with high stress depletes the mental resources necessary to attend to external prompts (Shah et al. 2012). Consequently, when stress is high, individuals are less receptive to salience shocks; their attention is already monopolized by immediate pressures, leaving fewer resources to process non-essential, pro-environmental information (Mani et al. 2013). This implies that the effectiveness of a green event in boosting attention diminishes as stress increases, as the 'tunneling' effect of scarcity limits the cognitive capacity needed to fully respond to the nudge (Mullainathan and Shafir 2013).

$$\frac{\partial^2 m}{\partial E\, \partial S} < 0. \tag{15}$$

The total effect of a change in S or E on green delivery is the product of its effect on m and the effect of m on $P(G)$. Therefore, the effect of physical stress S on the probability of choosing a green delivery option is

$$\frac{\partial P(G)}{\partial S} = \frac{\partial \Phi}{\partial m} \times \frac{\partial m}{\partial S} < 0. \tag{16}$$

Similarly, the effect of a green event is

$$\frac{\partial P(G)}{\partial E} = \frac{\partial \Phi}{\partial m} \times \frac{\partial m}{\partial E} > 0. \tag{17}$$

Based on our assumptions in Equations (12) and (15), the cross-effect is

$$\frac{\partial^2 P(G)}{\partial E\,\partial S} = \frac{\partial^2 \Phi}{\partial m^2} \times \frac{\partial m}{\partial E} \times \frac{\partial m}{\partial S} + \frac{\partial \Phi}{\partial m} \times \frac{\partial^2 m}{\partial E\,\partial S} < 0. \tag{18}$$

Equation (18) indicates that the marginal benefit of a green event decreases as physical stress increases.

4.3 Linking Theory and Evidence

The empirical patterns presented in the previous section can be coherently interpreted through the lens of our behavioral inattention framework. The systematic decrease in green delivery under physical stress, its increase during green awareness events, and the attenuation of the latter effect under high stress are all consistent with the proposed role of attention as a key mechanism. Below, we link each empirical finding to a specific component of our theoretical model.

First, the observed negative relationship between physical stress—such as air pollution, heat, and high electricity prices—and the take-up of green delivery aligns with the *cognitive scarcity* channel ($\partial m/\partial S < 0$). The framework posits that such stressors deplete cognitive resources, inducing a narrowing of attention toward immediate needs and away from future-oriented considerations (Mullainathan and Shafir 2013). The data confirm that as these pressures mount, households are more likely to prioritize immediate convenience over environmental benefits, consistent with a decrease in the attentional weight m assigned to the future.

Second, the significant rise in green delivery participation during sustainability campaigns supports the operation of the *salience shock* channel ($\partial m/\partial E > 0$). As proposed by the model, these events function by increasing the perceptual prominence of the environmental attribute (Bordalo et al. 2013). The results indicate that such interventions effectively shift attentional focus by reminding households of sustainability benefits, thereby increasing the salience of future benefits and temporarily raising m (Gabaix 2014, 2019). This suggests that pro-environmental preferences can be activated when the relevant attributes are made more accessible at the point of decision, although the effect is inherently temporary as the salience shock fades over time.

Third, the documented interaction, whereby the positive effect of green events is weaker under conditions of high physical stress, is explained by the mechanism of *attenuated salience effect under scarcity* ($\partial^2 m/\partial E \partial S < 0$). This finding indicates that cognitive scarcity not only reduces baseline attention to environmental goals but also constrains the processing of new, pro-social cues (Mani et al. 2013; Shah et al. 2012). When cognitive load is high, the capacity for attentional reallocation is diminished, limiting the effectiveness of external prompts.

Finally, our framework also accounts for the ancillary effects of order characteristics through the *immediate cost* channel, $u_0(a)$. The negative impacts of higher order value, size, and weight are explained by an increase in the perceived inconvenience of forgoing scheduling flexibility, which lowers $u_0(G)$. Conversely, greater green slot availability reduces this immediate cost by offering more convenient sustainable options, effectively increasing $u_0(G)$. These systematic patterns demonstrate that the model's core trade-off between immediate and future utility effectively captures a wider set of determinants beyond attention alone.

In summary, the framework provides a unified account of the evidence, positioning the allocation of attentional resources as a central determinant of pro-environmental choice. The results demonstrate that household contributions to the green transition are not solely a function of stable preferences, but are shaped in predictable ways by contextual factors that influence cognitive scarcity and salience.

5 Discussion

Our findings have direct implications for policymakers and firms aiming to encourage sustainable consumption, moving beyond conventional price-based or informational instruments. The central lesson is that the effectiveness of interventions depends critically on the cognitive context of the decision-maker. Policies must therefore be cognitively aware, aiming not only to provide incentives but also to manage the allocation of scarce attentional resources.

First, the finding that cognitive scarcity (e.g., from heat stress or pollution) significantly reduces green choices suggests that policymakers and firms should adopt a timing-sensitive approach to sustainability nudges. Deploying complex information or requests for pro-environmental effort during periods of high ambient stress is likely to be ineffective, as individuals' mental bandwidth is already depleted. Instead, green prompts and awareness campaigns should be strategically scheduled for periods when cognitive scarcity is lower, such as during milder weather conditions, to ensure the message can be received and processed.

Second, the demonstrated power of salience shocks highlights the value of well-designed public awareness campaigns. However, our framework adds a crucial caveat: the positive impact of these shocks is attenuated under high cognitive load. This implies that simply increasing the volume or frequency of messaging during crises will yield diminishing returns. Instead, the design of these interventions must be adapted. Under conditions of widespread stress (e.g., a heatwave), communications should be exceptionally simple, visual, and easy to process, minimizing cognitive effort. For online platforms, embedding immediate and salient feedback on environmental impact directly into the interface can serve as a persistent, low-cost reminder that functions as a continuous salience shock, helping to keep long-term goals top-of-mind even under stress.

More fundamentally, the interaction between scarcity and salience points to the superior strategy of building cognitive resilience directly into the choice architecture. Rather than relying solely on efforts to capture fluctuating attention, the goal should be to make the sustainable choice the path of least resistance. This can be achieved by setting 'cognitively-light' defaults, such as automatically opting customers into green delivery slots, while preserving the right to opt-out for convenience. Such a system would require minimal active attention and decision-making from the user, thereby making the green choice more robust to fluctuations in cognitive scarcity.

Thus, promoting sustainable consumption in an era of increasing climate-related stress could require a shift from a model of providing information to one of strategically managing attention. By timing interventions wisely, designing them for cognitive ease, and embedding sustainability into choice defaults, policymakers and firms can create systems that support pro-environmental behavior even when individual cognitive resources are stretched thin.

5.1 Robustness

To further validate our interpretation, we conduct a series of robustness checks to rule out alternative explanations.

5.1.1 Alternative Explanation: Driven by Slot Fee

We examine whether the environmental variables that predict green delivery systematically affect other dimensions of consumption behavior. If the observed effects operated through broad shifts in demand, income effects, or seasonal patterns, we would expect to see correlated changes in order value, basket size, order weight, or delivery preferences unrelated to environmental considerations. By contrast, if the effects reflect attention scarcity, then the impact should be specific to environmental outcomes and leave other aspects of shopping behavior unchanged.

Tables A4 through A7 report a battery of placebo tests. Table A4 examines the effect of air pollution on slot charges paid, order value, basket size, and order weight. These variables capture different facets of consumption that could be affected if pollution influenced disposable income, shopping frequency, or product categories. In all four cases, the coefficients are small and statistically insignificant. The absence of effects on slot charges rules out the possibility that consumers systematically adjust their willingness to pay for convenience during polluted days. Similarly, the null results for order value, basket size, and weight provide no evidence that pollution changes the composition of the customer base or induces substitution between product types. This pattern is consistent with a channel that narrows attention to environmental considerations, rather than one that reshapes consumption broadly.

Table A5 conducts the same tests using wet-bulb temperature as the key variable. Heat and humidity could plausibly affect shopping by reducing frequency (leading to larger consolidated orders), shifting product preferences (toward temperature-sensitive goods), or altering price sensitivity (due to discomfort). Yet none of these predictions materialize. Slot charges, order value, basket size, and order weight remain statistically unaffected by temperature stress. This lack of spillover is important: if heat stress generated general disutility from shopping, we would expect systematic adjustments in order composition. The fact that only green delivery choice responds reinforces our interpretation that heat stress crowds out environmental attention specifically.

Table A6 turns to temporary price cap (TPC) events. Because these events increase the salience of energy costs, one concern is that they may tighten household budgets or shift the timing of purchases. If this were the case, we would expect to observe smaller orders or greater price sensitivity during TPC periods. The results show otherwise. None of the four placebo outcomes move in response to TPC events. Spending levels, basket composition, and delivery charges are unaffected, providing clear evidence that TPCs operate through salience rather than through binding budget constraints. This distinction is important: if price caps worked by relaxing household budgets, we would expect to see compensatory changes in grocery spending. The absence of such adjustments strengthens our interpretation that cost salience primarily reallocates attention away from environmental concerns.

Table A7 examines the effects of environmental awareness campaigns. These events could have broader consequences if they attracted systematically greener customers with different shopping patterns, or if general promotional enthusiasm spilled over into unrelated choices. Yet again, all placebo outcomes remain unchanged. Slot charges, order value, basket size, and weight are unaffected, indicating that campaigns redirect attention toward environmental behavior at the moment of choice, rather than altering who shops or what they buy. This specificity is critical for interpretation: the campaigns change environmental salience without reshaping underlying consumption patterns.

Finally, Table A8 provides an additional robustness check by testing whether the platform itself systematically adjusts slot fees in response to environmental conditions. If the platform raised prices on polluted or hot days, or discounted during campaigns, our results could partly reflect supply-side pricing algorithms rather than consumer demand. The evidence rejects this possibility. Slot fees remain stable across all environmental variables, including pollution, temperature, TPC events, and awareness campaigns. This confirms that the observed patterns arise from consumer-side behavior rather than from platform-driven changes in incentives.

Taken together, these robustness tests demonstrate that the environmental variables we study do not affect consumption broadly. They do not alter willingness to pay for convenience, the value or size of orders, or the platform's pricing. Instead, the effects are specific to green delivery choice. This systematic null pattern across placebo outcomes provides strong support for our attention-based mechanism: environmental stressors crowd out cognitive bandwidth for sustainability considerations without altering household budgets, shopping frequency, or the supply-side environment.

5.1.2 Alternative Explanation: Driven by Time-of-Day Convenience

A potential concern with our identification strategy is that customers may select green delivery slots not due to environmental preferences, but simply because these slots happen to occur at convenient times of day. For instance, if green slots are disproportionately available during popular evening hours, our estimates could confound environmental preferences with time-of-day convenience preferences. To address this concern, we re-estimate all baseline regressions with an additional control variable: *slot_hr*, which captures the starting hour of each delivery time slot (ranging from 0 to 23). By including these hour-of-day fixed effects, we absorb any systematic patterns in demand related to delivery timing. This ensures that our identification comes from within-hour variation in green slot availability, conditional on the time of day. Table A presents the results. Across all specifications, adding the *slot_hr* control leaves our key coefficients virtually unchanged in both magnitude and statistical significance. This stability suggests that time-of-day convenience does not explain our findings. Customers' responsiveness to green slots reflects genuine environmental preferences rather than incidental preferences for particular delivery hours.

5.1.3 Green Event Placebo Test

The timing of promotional event effects provides important evidence for distinguishing attention-based mechanisms from alternative explanations such as learning or preference change. If events work by redirecting attention, their effects should be temporally precise, appearing on the day of exposure but not before or after. Persistent effects would suggest preference changes, while anticipatory effects would indicate confounding factors or measurement error. To test timing specificity, we implement placebo tests using the following specification:

$$\begin{aligned}\text{Green}_{i,t} = {} & \alpha + \beta_0 \,\text{HasEvent}_t + \beta_{-7}\,\text{HasEvent}_{t-7} + \beta_{+7}\,\text{HasEvent}_{t+7} \\ & + \beta_{-14}\,\text{HasEvent}_{t-14} + \beta_{+14}\,\text{HasEvent}_{t+14} + \beta_2\,\text{Proportion}_{i,t} + \beta_3\,\text{OrderChar}_{i,t} \\ & + \gamma_i + \delta_d + \theta_t + \eta_t + \varepsilon_{i,t}.\end{aligned} \tag{19}$$

Here, this specification includes the same-day event indicator (HasEvent_t) alongside placebo indicators shifted 7 and 14 days backward (lags) and forward (leads). The attention hypothesis predicts $\beta_0 > 0$ and $\beta_{-7} = \beta_{+7} = \beta_{-14} = \beta_{+14} = 0$. Non-zero placebo coefficients would suggest confounding factors, anticipatory behavior, or persistent preference changes rather than pure attention effects.

[Insert Table A2 and Table A3]

Table A2 and Table A3 examines timing by adding placebo indicators that shift HasEvent seven or fourteen days backward or forward. The goal is to examine pre-trends or persistence. Column 1 includes lag14 only, and Column 3 includes lead14 only. Columns 2 and 4 include HasEvent jointly with lag14 or lead14, respectively. In both joint specifications, the same-day HasEvent coefficient is positive and significant, and the lag or lead term is small and not significant. Column 5 includes the full joint specification with HasEvent, lag7, lead7, lag14, and lead14.

The evidence shows that the effect of salience is confined to the day of exposure, with no indication of anticipatory movement or post-event drift. This timing is consistent with an attention-based mechanism rather than gradual shifts in preferences. The same-day *HasEvent* effect remains stable (around 0.07) across all specifications, while all lead and lag terms are statistically indistinguishable from zero. This precise timing pattern is what we would expect from an attention-based mechanism: promotional events redirect focus toward sustainability on the day of exposure, but the effect dissipates quickly as other concerns reclaim attention.

6 Conclusion

In this paper, we have shown that environmental stress reduces pro-social behavior in the domain of climate mitigation. Using transaction-level evidence from a large online supermarket, we find that air pollution, heat, and electricity price salience lower the likelihood of choosing green delivery, a low-cost action that benefits the collective but requires giving up private convenience. Independent environmental campaigns substantially increase green delivery adoption. Because these campaigns are unrelated to the platform's delivery service, they provide clean evidence that salience shocks can redirect attention toward sustainability and offset the effects of stress.

There are three main contributions. First, it provides the first evidence on how limited attention affects household contributions to environmental public goods, extending the literature on cognitive scarcity beyond private economic outcomes. Second, it contributes to environmental economics by identifying real-time behavioral frictions that weaken the effectiveness of climate policy instruments. Third, it advances the study of collective action by showing how attention scarcity shapes participation in the provision of public goods. Together, the findings highlight the importance of designing policies that sustain household contributions under cognitive constraints.

Our results extend the literature on cognitive scarcity by showing that attentional limits erode pro-social contributions to public goods, not only private outcomes. They also highlight an overlooked cost of environmental degradation: pollution and heat weaken the behavioral foundations of collective action against climate change. From a policy perspective, interventions that preserve or redirect attention, such as campaigns, reminders, or defaults, can complement price-based instruments in sustaining household contributions to the green transition.

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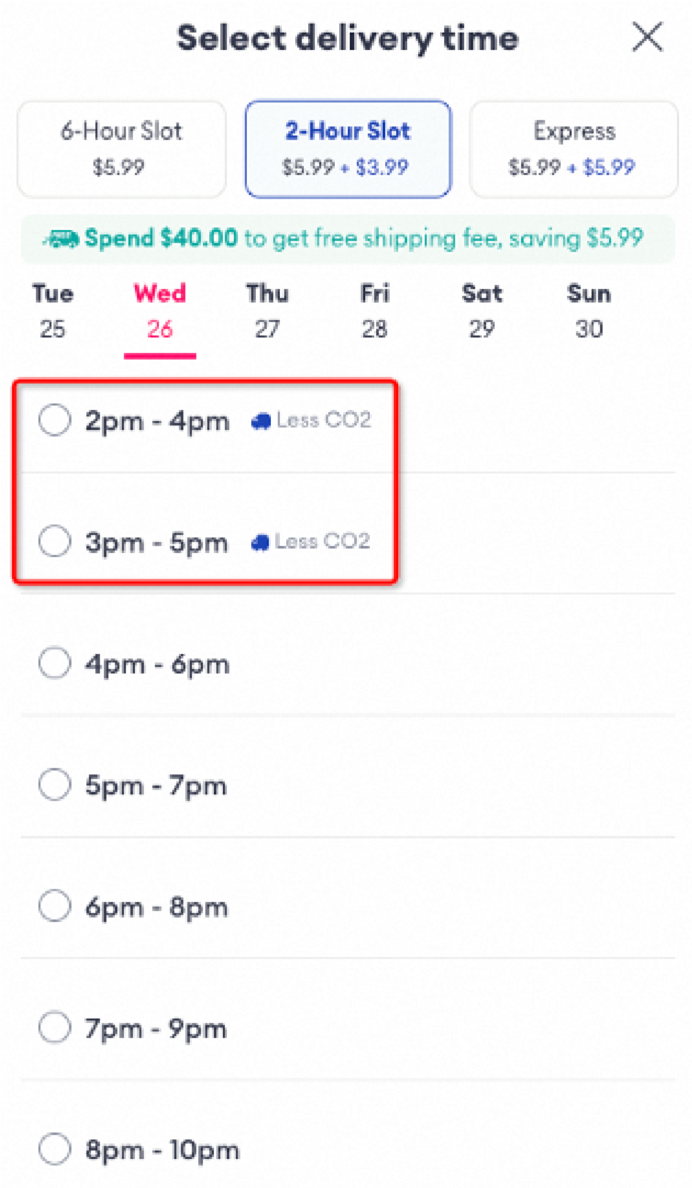
Figure 1: Screenshot



Notes. App user interface of selecting delivery time slots.

Table 1: Summary Statistics

Var.	**Def.**	**Obs**	**Mean**	**SD**	**Min**	**Max**
Panel A: Delivery characteristics						
green	1 = choosing green option, 0 = choose non-green options.	36,907	0.386	0.487	0.000	1.000
proportion	Green option percentage, = eco avail entries/avail entries	36,907	0.236	0.191	0.006	1.000
expensive	1 = expensive if price band range is in [100_), 0 = else	36,907	0.569	0.495	0.000	1.000
avail entries	number of available delivery time slots	36,907	16.783	21.268	1.000	187.000
eco entries	number of green delivery time slots	36,907	2.914	2.967	1.000	77.000
eco avail entries	number of available green delivery time slots	36,907	2.205	2.286	1.000	77.000
charged entries	number of time slots that are charged (not free)	36,907	10.228	16.799	0.000	171.000
charged avail entries	number of available time slots that are charged	36,907	10.188	16.780	0.000	171.000
shipping fee	shipping fee paid for the order	36,907	0.214	1.104	0.000	10.000
slot fee	slot charges in SGD	36,907	0.487	1.405	0.000	5.990
order weight	weight of the order in kg	36,907	25.568	24.799	0.150	1,035.000
qty	sum (quantity of each item)	36,907	20.553	15.740	1.000	210.000
Panel B: Meteorological Data						
TPC	1 = TPC if the temporary price cap is triggered, 0 = else.	28,527	0.058	0.234	0.000	1.000
Twb	the district-level wet-bulb temperature	36,907	25.069	0.751	22.010	27.540
PSI	a number used to indicate the level of pollutants in air.	36,907	45.424	11.972	14.292	108.375
HasEvent	1 = HasEvent if any green event takes place on that date, 0 = else.	36,907	0.086	0.280	0.000	1.000

Notes. This table presents the summary statistics used in our sample. The sample period is from March 2023 to March 2025.

Table 2: Air Pollution (PSI)

	Dependent variable: green		
	(1)	(2)	(3)
	green	green	green
PSI	-0.0015**	-0.0012**	-0.0013**
	(0.0006)	(0.0006)	(0.0006)
proportion		0.4732***	0.4468***
		(0.0350)	(0.0348)
expensive			-0.0888***
			(0.0161)
qty			-0.0028***
			(0.0006)
order weight			-0.4689
			(0.4439)
slot fee			-0.0403***
			(0.0046)
Constant	0.4723***	0.3435***	0.5002***
	(0.0291)	(0.0301)	(0.0332)
Individual FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Observations	10,985	10,985	10,981
R-squared	0.5100	0.5246	0.5359
Adj. R-squared	0.1292	0.1550	0.1746

Note. This table presents the impact of air pollution on consumer green choice. The Pollutant Standards Index (PSI) is an air-quality index used in Singapore that indicates the level of pollutants in air. To match the consumer district, we combine district definitions from NEA, URA, and common knowledge of the south area. All columns include individual, district, day-of-week, and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Wet-bulb Temperature

	Dependent variable: green			
	(1)	(2)	(3)	(4)
	green	green	green	green
Twb	-0.0433***	-0.0414***	-0.0410***	-0.0364**
	(0.0124)	(0.0122)	(0.0121)	(0.0157)
proportion		0.4736***	0.4471***	0.9021
		(0.0350)	(0.0347)	(0.9963)
Twb ×proportion				-0.0181
				(0.0397)
expensive			-0.0884***	-0.0885***
			(0.0161)	(0.0161)
qty			-0.0028***	-0.0028***
			(0.0006)	(0.0006)
order weight			-0.4467	-0.4471
			(0.4449)	(0.4449)
slot fee			-0.0404***	-0.0404***
			(0.0046)	(0.0046)
Constant	1.4905***	1.3228***	1.4693***	1.3549***
	(0.3112)	(0.3063)	(0.3027)	(0.3935)
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,981	10,981	10,981
R-squared	0.5106	0.5252	0.5365	0.5365
Adj. R-squared	0.1302	0.1561	0.1756	0.1755

Note. This table presents the impact of the calculated wet-bulb temperature on consumer green choice. *Twb* denotes the district-level wet-bulb temperature, a proxy for heat stress combining air temperature and relative humidity. The wet-bulb temperature T_w is approximated from dry-bulb temperature T (in °C) and relative humidity RH (in %) using (Stull, 2011). All columns include individual, district, day-of-week, and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Electricity Prices (TPC)

	Dependent variable: green		
	(1)	(2)	(3)
	green	green	green
TPC	-0.0682**	-0.0711**	-0.0701**
	(0.0339)	(0.0339)	(0.0338)
proportion		0.4505***	0.4267***
		(0.0431)	(0.0431)
expensive			-0.0733***
			(0.0200)
qty			-0.0030***
			(0.0007)
order weight			-0.5021
			(0.5528)
slot fee			-0.0365***
			(0.0056)
Constant	0.4168***	0.3049***	0.4531***
	(0.0020)	(0.0108)	(0.0209)
Individual FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Observations	7,185	7,183	7183
R-squared	0.5257	0.5384	0.5481
Adj. R-squared	0.1294	0.1526	0.1696

Note. TPC equals 1 if the temporary price cap is triggered, and 0 otherwise. All columns include individual, district, day-of-week, and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Singapore Green Events

	Dependent variable: green					
	(1)	(2)	(3)	(4)	(5)	(6)
	green	green	green	green	green	green
HasEvent	0.0579***	0.0392***	0.0369*	0.0526***	0.0700*	0.0113
	(0.0092)	(0.0088)	(0.0216)	(0.0143)	(0.0373)	(0.0451)
HasEvent × proportion						0.2175**
						(0.0945)
proportion		0.5056***	0.4457***	0.5097***	0.4473***	0.426***
		(0.0127)	(0.0350)	(0.0127)	(0.0348)	(0.037)
expensive		-0.0644***	-0.0911***	-0.0659***	-0.0892***	-0.089***
		(0.0058)	(0.0162)	(0.0058)	(0.0161)	(0.016)
qty		-0.0031***	-0.0028***	-0.0031***	-0.0028***	-0.003***
		(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.001)
order weight		0.3106***	-0.3835	0.3284***	-0.4522	-0.438
		(0.1063)	(0.4459)	(0.1064)	(0.4448)	(0.445)
slot fee		-0.0360***	-0.0392***	-0.0369***	-0.0402***	-0.040***
		(0.0014)	(0.0046)	(0.0014)	(0.0046)	(0.005)
Constant	0.3810***	0.3724***	0.4391***	0.3722***	0.4357***	0.4412***
	(0.0027)	(0.0058)	(0.0176)	(0.0059)	(0.0178)	(0.0180)
Individual FE	No	No	Yes	No	Yes	Yes
District FE	No	Yes	Yes	Yes	Yes	Yes
Day of week FE	No	No	No	Yes	Yes	Yes
Year-month FE	No	No	No	Yes	Yes	Yes
Observations	36,907	36,887	10,981	36,887	10,981	10,981
R-squared	0.0011	0.1008	0.5330	0.1055	0.5359	0.5362
Adj. R-squared	0.0011	0.0988	0.1734	0.1028	0.1745	0.1749

Note. HasEvent equals 1 if any green event takes place on that date; otherwise 0. For the list of events, see Appendix Table A1. Column (4)-(6) control for day-of-week, and year-month fixed effects. Column (3),(5),(6) include individual fixed effexts and column(2)-(6) all control for district fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Effect of Wet-bulb Temperature and Pollution on Green Delivery Choice

	(1) green	(2) green	(3) green	(4) green
Panel A: Twb				
Twb	-0.0420***	-0.0335***	-0.0400***	-0.0316**
	(0.0124)	(0.0128)	(0.0121)	(0.0125)
HasEvent	0.0765**	2.3366***	0.0642*	2.2902***
	(0.0381)	(0.7795)	(0.0372)	(0.7864)
HasEvent × Twb		-0.0903***		-0.0890***
		(0.0311)		(0.0314)
Other Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,985	10,981	10,981
R-squared	0.5110	0.5116	0.5367	0.5374
Panel B: PSI				
PSI	-0.0014**	-0.0009	-0.0012**	-0.0007
	(0.0006)	(0.0007)	(0.0006)	(0.0006)
HasEvent	0.0808**	0.3486***	0.0684*	0.3476***
	(0.0382)	(0.1003)	(0.0373)	(0.0968)
HasEvent × PSI		-0.0057***		-0.0059***
		(0.0020)		(0.0019)
Other Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,985	10,981	10,981
R-squared	0.5104	0.5111	0.5362	0.5369

Notes: This table presents the effect of wet-bulb temperature and pollution on green dilivery choice. *Twb* in Panel A denotes the district-level wet-bulb temperature, a proxy for heat stress combining air temperature and relative humidity. The Pollutant Standards Index (PSI) in Panel B is an air-quality index used in Singapore that indicates the level of pollutants in air. All specifications include individual, district, day-of-week, and year–month fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Drivers of Green Delivery (Order level)

	Dependent variable: green							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	green	green	green	green	green	green	green	green
proportion	0.5438***	0.5668***	0.5882***	0.5763***	0.4837***	0.5985***	0.5313***	0.4593***
	(0.0180)	(0.0209)	(0.0181)	(0.0131)	(0.0522)	(0.0567)	(0.0514)	(0.0361)
expensive	-0.1180***				-0.1146***			
	(0.0076)				(0.0219)			
expensive × proportion	0.0863***				-0.0021			
	(0.0249)				(0.0647)			
qty		-0.0037***				-0.0024***		
		(0.0003)				(0.0007)		
proportion × qty		0.0013				-0.0053***		
		(0.0009)				(0.0020)		
order_weight			-0.4735***				-1.1333**	
			(0.1646)				(0.5712)	
proportion × order_weight			0.2605				-1.9969	
			(0.5412)				(1.5495)	
slot_fee				-0.0153***				-0.0214***
				(0.0021)				(0.0067)
proportion × slot_fee				-0.1057***				-0.0756***
				(0.0098)				(0.0271)
Constant	0.3132***	0.3218***	0.2577***	0.2641***	0.3555***	0.3413***	0.3118***	0.3037***
	(0.0059)	(0.0064)	(0.0056)	(0.0042)	(0.0160)	(0.0191)	(0.0161)	(0.0097)
Individual FE	No	No	No	No	Yes	Yes	Yes	Yes
District FE	No	No	No	No	Yes	Yes	Yes	Yes
Day of week FE	No	No	No	No	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.0645	0.0665	0.0549	0.0637	0.5291	0.5287	0.5259	0.5284
Adj. R-squared	0.0645	0.0664	0.0548	0.0636	0.1628	0.1621	0.1571	0.1616
Observations	36907	36907	36888	36907	10985	10985	10981	10985

Notes. This table presents the drivers of green delivery based on order-level data. The dependent variable *green* is whether consumers choose the green option. *Proportion* is the percentage of green option in all options. *Expensive* is measured by the total order price, if it is greater than or equal to 100, it equals to 1,and 0 otherwise. *Qty* is the sum quantity of each item. *Order weight* is weight of the order in kg. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Column (1) represents the effect of order price on consumer green choice. Column (2) represents the effect of item quantity on consumer green choice. Column (3) explains the effect of order weight on consumer green choice. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix

Not Intended for Publication

A Additional Tables and Figures

Table A1: Listing of Events

Start Date	End Date	Year	Month	Day	EventName	Category	Description	Duration Days
2023/5/13	2023/5/13	2023	5	13	SG Clean Day - Islandwide Clean Up	Environment	Record-breaking community clean-up under Public Hygiene Council	1
2023/9/14	2023/9/14	2023	9	14	Recycle Right Campaign Update 2023	Environment	NEA update encouraging correct recycling; household recycling survey release	1
2023/9/16	2023/9/16	2023	9	16	World Cleanup Day SG 2023	Environment	Global cleanup day observed across Singapore	1
2023/10/14	2023/10/14	2023	10	14	International E-waste Day activation (NEA)	Environment	NEA e-waste awareness activation at Toa Payoh HDB Hub	1
2023/11/4	2023/11/4	2023	11	4	Clean & Green Singapore Day 2023	Environment	National CGS Day with community activities and tree-planting	1
2023/12/15	2023/12/15	2023	12	15	GreenGov.SG Report (Inaugural)	Environment	Public sector sustainability performance report released	1
2024/3/4	2024/3/4	2024	2	10	Green Plan 2030 - COS Update 2024	Environment	Committee of Supply speech / Green Plan progress highlights	1
2024/6/12	2024/7/14	2024	6	12	Go Green SG 2024	Environment	Nationwide sustainability movement; many public events	33
2024/6/14	2024/7/22	2024	6	14	Singapore Oil Spill Response	Weather/ Environment	Collision-led fuel oil spill; response and phased beach reopening	39
2024/6/24	2024/6/24	2024	6	24	NEA Update: Bulk Oil Removal Near Completion	Weather/ Environment	NEA update on oil removal progress; shift to specialised cleanup	1

Continued on next page

Table A1: Listing of Events (continued)

Start Date	**End Date**	**Year**	**Month**	**Day**	**EventName**	**Category**	**Description**	**Duration Days**
2024/7/13	2024/7/30	2024	7	13	Dry Spell (18 days)	Weather	18 consecutive days with <1.0 mm rainfall; respite end July	18
2024/9/20	2024/9/20	2024	9	20	World Cleanup Day SG 2024	Environment	Global cleanup day	1
2024/11/3	2024/11/3	2024	11	3	Clean & Green Singapore Day 2024	Environment	Environmental stewardship day; community and hygiene focus	1
2024/11/18	2024/11/18	2024	11	18	GreenGov.SG Report FY2023	Environment	Annual public sector sustainability performance report release	1
2025/1/10	2025/1/13	2025	1	10	Northeast Monsoon Surge Advisory Window	Weather	NEA advisory: monsoon surge bringing cool rainy conditions	4

Notes. This hand-collected table summarizes the green events which took place during our sample period.

Table A2: Singapore Green Events - Placebo Tests

	Dependent variable: green							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lag7	lag7	lag7_joint	lag7_joint	lead7	lead7	lead7_joint	lead7_joint
HasEvent			0.0487***	0.0710*			0.0488***	0.0714*
			(0.0143)	(0.0370)			(0.0143)	(0.0370)
HasEvent_lag7	0.2169	0.1445	0.2134	0.1434				
	(0.1393)	(0.1862)	(0.1385)	(0.1820)				
HasEvent_lead7					0.0497	-0.3062	0.0450	-0.3125
					(0.2383)	(0.2322)	(0.2358)	(0.2303)
proportion	0.5467***	0.4452***	0.5456***	0.4437***	0.5465***	0.4462***	0.5454***	0.4447***
	(0.0127)	(0.0346)	(0.0127)	(0.0346)	(0.0127)	(0.0347)	(0.0127)	(0.0347)
expensive	-0.0605***	-0.0887***	-0.0604***	-0.0890***	-0.0605***	-0.0886***	-0.0604***	-0.0889***
	(0.0059)	(0.0161)	(0.0059)	(0.0161)	(0.0059)	(0.0161)	(0.0059)	(0.0161)
qty	-0.0029***	-0.0027***	-0.0029***	-0.0027***	-0.0029***	-0.0027***	-0.0029***	-0.0027***
	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)
order weight	0.4306***	-0.4798	0.4327***	-0.4711	0.4292***	-0.4942	0.4314***	-0.4856
	(0.1092)	(0.4469)	(0.1092)	(0.4472)	(0.1091)	(0.4469)	(0.1092)	(0.4471)
slot fee	-0.0339***	-0.0407***	-0.0340***	-0.0408***	-0.0339***	-0.0408***	-0.0340***	-0.0408***
	(0.0015)	(0.0046)	(0.0015)	(0.0046)	(0.0015)	(0.0046)	(0.0015)	(0.0046)
Constant	0.3568***	0.4415***	0.3530***	0.4355***	0.3569***	0.4412***	0.3530***	0.4352***
	(0.0058)	(0.0174)	(0.0059)	(0.0177)	(0.0058)	(0.0174)	(0.0059)	(0.0177)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
District FE	No	Yes	No	Yes	No	Yes	No	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,888	10,983	36,888	10,983	36,888	10,983	36,888	10,983
R-squared	0.0836	0.5330	0.0839	0.5333	0.0836	0.5330	0.0839	0.5333
Adj. R-squared	0.0827	0.1756	0.0830	0.1760	0.0827	0.1757	0.0829	0.1761

Note. The table reports a robustness test of green events' impact on consumer green choice. Columns (1) - (8) use ±7-day placebo indicators; columns (5) - (9) include *HasEvent* jointly with each placebo. Column (1),(3),(5),(7) control for day-of-week fixed effects and year-month fixed effects. Column (2),(4),(6),(8) control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Singapore Green Events - Placebo Tests

	Dependent variable: green							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lag14	lag14	lag14_joint	lag14_joint	lead14	lead14	lead14_joint	lead14_joint
HasEvent			0.0488***	0.0714*			0.0488***	0.0704*
			(0.0143)	(0.0371)			(0.0143)	(0.0371)
HasEvent_lag14	-0.0343	0.0422	-0.0347	0.0615				
	(0.1689)	(0.2218)	(0.1690)	(0.2195)				
HasEvent_lead14					-0.0633	-0.2639	-0.0676	-0.2565
					(0.1601)	(0.2558)	(0.1585)	(0.2554)
proportion	0.5466***	0.4447***	0.5455***	0.4431***	0.5466***	0.4434***	0.5454***	0.4420***
	(0.0127)	(0.0346)	(0.0127)	(0.0346)	(0.0127)	(0.0346)	(0.0127)	(0.0346)
expensive	-0.0605***	-0.0889***	-0.0604***	-0.0891***	-0.0605***	-0.0890***	-0.0604***	-0.0893***
	(0.0059)	(0.0161)	(0.0059)	(0.0161)	(0.0059)	(0.0161)	(0.0059)	(0.0161)
qty	-0.0029***	-0.0027***	-0.0029***	-0.0027***	-0.0029***	-0.0027***	-0.0029***	-0.0027***
	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)
order weight	0.4290***	-0.4872	0.4312***	-0.4784	0.4290***	-0.4894	0.4312***	-0.4807
	(0.1091)	(0.4468)	(0.1091)	(0.4471)	(0.1091)	(0.4467)	(0.1091)	(0.4470)
slot fee	-0.0339***	-0.0408***	-0.0340***	-0.0408***	-0.0340***	-0.0409***	-0.0340***	-0.0409***
	(0.0015)	(0.0046)	(0.0015)	(0.0046)	(0.0015)	(0.0046)	(0.0015)	(0.0046)
Constant	0.3569***	0.4416***	0.3530***	0.4356***	0.3569***	0.4421***	0.3530***	0.4362***
	(0.0058)	(0.0174)	(0.0060)	(0.0177)	(0.0058)	(0.0174)	(0.0060)	(0.0177)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
District FE	No	Yes	No	Yes	No	Yes	No	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,888	10,983	36,888	10,983	36,888	10,983	36,888	10,983
R-squared	0.0836	0.5330	0.0839	0.5333	0.0836	0.5331	0.0839	0.5334
Adj. R-squared	0.0827	0.1755	0.0829	0.1759	0.0827	0.1757	0.0829	0.1761

Note. The table reports a robustness test of green events' impact on consumer green choice. Columns (1) - (8) use ±14-day placebo indicators; columns (5) - (9) include *HasEvent* jointly with each placebo. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Effect of Air Pollution on Other Consuming Choices

	Independent variable: PSI			
	(1) slot fee	(2) expensive	(3) qty	(4) order weight
PSI	-0.00172	0.000347	0.0133	-0.00811
	(0.00155)	(0.000536)	(0.0150)	(0.0193)
Constant	0.521***	0.610***	22.73***	24.94***
	(0.0714)	(0.0247)	(0.692)	(0.887)
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,985	10,985	10,981
R-squared	0.575	0.629	0.745	0.737

Note. The table presents the effect of air pollution on other consuming choices. *slot fee* represents slot charges in sgd. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

Table A5: Effect of Wet-bulb Temperature on Other Consuming Choices

	Independent variable: Twb			
	(1) slot fee	(2) expensive	(3) qty	(4) order weight
Twb	-0.0350	0.0116	0.242	0.412
	(0.0312)	(0.0106)	(0.296)	(0.385)
Constant	1.318*	0.335	17.26**	14.24
	(0.782)	(0.265)	(7.429)	(9.658)
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,985	10,985	10,981
R-squared	0.575	0.629	0.745	0.737

Note. The table presents the effect of wet-bulb temperature on other consuming choices. *slot fee* represents slot charges in sgd. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Effect of Electricity Prices on Other Consuming Choices

	Independent variable: TPC			
	(1)	(2)	(3)	(4)
	slot fee	expensive	qty	order weight
TPC	0.0404	-0.00485	-0.0246	-0.254
	(0.0848)	(0.0295)	(0.833)	(1.109)
Constant	0.417***	0.617***	23.17***	23.96***
	(0.00509)	(0.00177)	(0.0500)	(0.0665)
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	7,185	7,185	7,185	7,183
R-squared	0.560	0.638	0.745	0.746

Note. The table presents the effect of electricity prices on other consuming choices. *slot fee* represents slot charges in sgd. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Effect of Green Event on Other Consuming Choices

Independent variable: HasEvent				
	(1) slot fee	(2) expensive	(3) qty	(4) order weight
HasEvent	0.0385	-0.00149	-1.390	-1.327
	(0.0925)	(0.0311)	(0.982)	(1.147)
Constant	0.439***	0.626***	23.45***	24.68***
	(0.00763)	(0.00256)	(0.0810)	(0.0946)
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,985	10,985	10,981
R-squared	0.575	0.629	0.745	0.737

Note. The table presents the effect of Singapore green events on other consuming choices. *slot fee* represents slot charges in sgd. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Effect of Environmental Factors on Slot Fee

	Dependent variable: slot fee			
	(1)	(2)	(3)	(4)
	slot fee	slot fee	slot fee	slot fee
Psi	-0.00172			
	(0.00155)			
Twb		-0.0350		
		(0.0312)		
TPC			0.0404	
			(0.0848)	
HasEvent				0.0385
				(0.0925)
Constant	0.521***	1.318*	0.417***	0.439***
	(0.0714)	(0.782)	(0.00509)	(0.00763)
Individual FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observations	10,985	10,985	7,185	10,985
R-squared	0.575	0.575	0.560	0.575

Note. The table presents the effect of environmental factors on slot fee. *slot fee* represents slot charges in sgd. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Robustness: Wet-bulb Temperature (ln Twb)

	Dependent variable: green		
	(1)	(2)	(3)
	green	green	green
Ln_Twb	-1.0895***	-1.0364***	-0.9989***
	(0.3021)	(0.2978)	(0.2959)
proportion		0.4576***	0.4634***
		(0.0352)	(0.0349)
expensive			-0.0864***
			(0.0159)
qty			-0.0026***
			(0.0006)
order weight			-0.3801
			(0.4350)
Constant	3.9139***	3.6282***	3.6307***
	(0.9731)	(0.9592)	(0.9530)
Individual FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Observations	10,985	10985	10,981
R-squared	0.5263	0.5396	0.5464
Adj. R-squared	0.1570	0.1805	0.1922

Note. This table presents the robustness test of wet-bulb temperature. This table use ln(Twb) to measure the wet-bulb temperature and test its impact on consumer green choice. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A10: The effect of google trend on green preference

	Dependent variable: green	
	(1)	(2)
	green	green
trend_green	0.0029**	
	(0.0015)	
sustainability		0.0013**
		(0.0006)
proportion2	0.4479***	0.4475***
	(0.0348)	(0.0371)
expensive1	-0.0888***	-0.0838***
	(0.0161)	(0.0171)
qty	-0.0028***	-0.0026***
	(0.0006)	(0.0007)
order_weight	-0.4577	-0.5305
	(0.4450)	(0.4680)
slot_fee	-0.0402***	-0.0418***
	(0.0046)	(0.0048)
Constant	0.2243**	0.3781***
	(0.1114)	(0.0350)
Individual FE	Yes	Yes
District FE	Yes	Yes
Day of week FE	Yes	Yes
Year-Month FE	Yes	Yes
R-squared	0.5359	0.5394
Adj. R-squared	0.1745	0.1756
Observations	10,981	9,936

Note. This table presents the ffect of google trend on green preference. This table uses Google trend index to measure the human attention and test its impact on consumer green choice. All the columns control for individual fixed effects, district fixed effects, day-of-week fixed effects and year-month fixed effects. Standard errors in parentheses are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.