THE CLIMATE OF CHOICE

HOW WEATHER CONDITIONS SHAPE CONSUMER DECISION-MAKING

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Bachelor Thesis

Stockholm School of Economics

2025

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Abstract:

How does the weather affect consumer decision-making? This thesis examines whether consumers of public transport behave in line with the rational benchmark when choosing from a menu of contracts, and whether certain weather conditions systematically affect these decisions. Using a panel dataset of consumer purchases from Västtrafik's To Go app combined with daily weather data from the Swedish Hydrological and Meteorological Institute, we investigate overspending behavior and estimate fixed-effects regressions to observe weather-induced projection bias. We find that 1.8–2.7% of Adults and around 0.5% of Youths systematically overspend on single tickets over a 30-day period, compared to the price of a flat-rate ticket, resulting in an annual welfare loss exceeding SEK 7 million. Abnormally warm days reduce the purchases of 30-day tickets by 1.2%, while two-day lagged precipitation increases them by 14.7% per millimeter. Precipitation also positively affects the probability of overspending by 4.0% per millimeter. Other than these findings, most weather variables show no meaningful effects. These results suggest that, while most consumers' decision-making aligns with the rational benchmark, a subset exhibits only bounded rationality. These findings extend the behavioral finance literature by documenting these biases and challenging the neoclassical assumption of rational consumer behavior in a new context.

Keywords:

Menu of contracts, rational model, projection bias, welfare, weather.conditions.

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Bachelor Thesis
Bachelor Program in Business & Economics
Stockholm School of Economics
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How does the weather affect consumer decision-making? Some firms providing services offer a menu of contracts, a list of choices the consumer is to choose from. Cell-phone carriers offer a trade-off between data plans and price, and gyms offer different types of memberships including subscription services, single tickets, or multiple day passes. The neoclassical literature in financial economics assumes that individuals have rational expectations about their future consumption and that their present contract choices maximize their future utility, given those expectations. This is an essential part of the fundamental Capital Asset Pricing Model established by William F. Sharpe (1964), which formalizes how rational investors construct optimal portfolios under risk.[1] Similarly, in Robert E. Lucas, Jr. (1978), the author presents a consumption-based asset pricing framework in which expectations of rational consumers about future consumption shape their decision-making.[2] Both papers rely on the assumption that consumers are rational and forward-looking. More recent literature has provided evidence challenging the validity of this assumption, and in this thesis, we add to this evidence by investigating how weather conditions affect consumer decision-making behavior when choosing from a menu of contracts for public transport services. We do so by answering the following two questions:

1. Do consumers of public transport overspend on single tickets, i.e., spend more on them than the price of a period ticket, due to an inaccurate expectation of future consumption?
2. Do weather conditions affect the demand for specific public transport ticket types, and do they affect any potential overspending on single tickets?

We expect there to be a small systematic overspending on single tickets, which we define as any money spent on single tickets in a given period above the price of a flat-fee ticket for the same period. Such a finding would align with the evidence provided by DellaVigna & Malmendier (2006), presenting how gym members tend to overestimate their future attendance, leading to paying higher prices per visit.[3] We investigate almost the opposite effect, whether consumers of public transport *underestimate* their future consumption, potentially leading to overspending, due to a similar inaccuracy in consumer expectations of future consumption and behavior. Hence, we also expect there to be a systematic level of overspending on single tickets in the public transport industry. Furthermore, we expect consumers' contractual choices to be influenced by weather conditions, as observed in Busse, Pope, Pope & Silva-Risso (2015), where warmer days prompted car buyers to purchase convertibles rather than four-wheel drive vehicles.[4] We expect a similar projection bias in the public transport industry, and that a similar weather effect could affect potential overspending.

Any failure by consumers to minimize their cost (overspending) or any significant weather effect on their decision-making indicates a deviation from the rational model benchmark and a violation of at least one of its three assumptions: 1) Perfect foresight, 2) Utility maximization (cost minimization), and 3) No bias.[5] Although we assume consumers are inherently looking to minimize their costs, hence, deviations are due to

[1] Sharpe, "Capital Asset Prices."
[2] Lucas, "Asset Prices in an Exchange Economy."
[3] DellaVigna and Malmendier, "Paying Not to Go to the Gym."
[4] Busse et al., "The Psychological Effect of Weather on Car Purchases."
[5] Tirole, "The Theory of Industrial Organization."

violations of assumptions 1 and/or 3, which may in turn lead to failure in aligning with assumption 2.

Our findings are of importance to consumers of public transport as they highlight how consumers systematically misjudge their future travel needs and lead them to bear unnecessary financial costs, resulting in a welfare loss. This loss is synonymous with profit for the public transport provider, indicating that they systematically benefit from consumers' lack of rationality. This raises questions about fairness and transparency that would point to the opportunity to explore the implementation of a more consumer-friendly menu of contracts or a 'capping' mechanism. Our thesis could also serve as help in consumers' decision-making by making them more mindful of how they make their choices, so that they could become more aware of any potential lack of rationality in their process.

In our thesis, we follow a similar structure to the one presented in DellaVigna & Malmendier (2006), where we make predictions in relation to the rational model and test whether the behavior exhibited by consumers aligns with its assumptions, but our methodology also differs in some ways.[6] DellaVigna & Malmendier rely mostly on straightforward benchmark comparisons, similar to our cost-comparison and overspending tests, but we also extend the analysis by running regressions to examine if weather conditions specifically have a systematic effect on ticket choices and overspending. This allows us to go beyond the question of *whether* rational behavior is violated and investigate *why* or *what mechanisms* are behind the behavioral deviations.

We use consumer data provided by Västtrafik, the public transport provider for the Västra Götaland region in Sweden, in the form of an anonymous panel dataset, which alone allows us to observe the quantity of purchases of tickets and any potential overspending on single tickets. We also hand-picked weather data from the public website for the Swedish Hydrological and Meteorological Institution for insights on daily temperature, precipitation, sunshine hours, and cloud cover. With the use of these datasets, we run logarithmic and logistic regressions with individual fixed effects to see if weather conditions bear any systematic effect on the decision to purchase specific ticket types and if it affects overspending. We also perform robustness checks in the form of permutation tests for our findings to test whether the results are significant due to an existing effect or simply due to randomness.

While the data we use provides for a solid analysis on consumer decision-making and how weather affects it, we lack more detailed individual-specific data to control for individual differences that are potential underlying reasons for specific behavior, such as home addresses, specific transport alternatives, or household income. As we cannot control for these variables, our experiment on the effect of weather is limited, as it lacks the isolation that would be found in an ideal experiment.

Nevertheless, our results provide a clear picture of how consumers of Västtrafik's services behave relative to the rational benchmark. We find that between 1.8% and 2.7% of Adults and around 0.5% of Youths systematically overspend on single tickets over a 30-day period, compared to the price of a flat-rate ticket. Indicating a failure to cost-minimize due to inaccurate expectations of future travel needs. These deviations suggest a lack of

[6] DellaVigna and Malmendier, "Paying Not to Go to the Gym."

perfect foresight and potential bias in consumers' expectations and purchasing decisions. The overspending results in an annual welfare loss exceeding SEK 7 million for overspenders.

We also find that certain weather conditions influence ticket choices in ways consistent with projection bias, essentially a form of weather-induced projection bias. Specifically, abnormally high temperatures seem to decrease the purchases of 30-day tickets, while precipitation two days prior to the day of purchase seems to increase them. This suggests consumers systematically respond to weather when forming their expectations of future consumption, experiencing a form of bias from external factors outside of their own expectations. However, most weather variables show no effect, indicating that only specific, sufficiently salient weather conditions affect consumer decision-making. We also observe certain seasonal patterns, indicating changes in weather effect throughout the year. In the spring/early summer, higher sunshine hours increase single ticket purchases, while this effect of sunshine hours is negative when considering the overall sample period. Moreover, precipitation seems to increase the probability of overspending on single tickets, suggesting that weather not only affects contract choices, but also has financial consequences for consumers.

Since the deviations and effects we observe are modest in size and rather selective, our findings point to bounded rationality rather than full-on irrationality. Most consumers behave in line with the rational benchmark, while a smaller subset shows deviations from it.

As previously mentioned, neoclassical literature assumes rationality of consumers, which is something we investigate in our thesis by following the ideas presented in the current behavioral finance body of work and build on the existing literature with new insights from the public transport industry and a deeper investigation of weather effects.

Chetty, Looney & Kroft (2009) provide an analysis on how consumers systematically deviate from rational price and cost-minimization when the tax component of prices is not salient. [7] They provide evidence that consumers respond almost entirely to the posted shelf price rather than the full post-tax price, despite it being their total cost. Consumers essentially behave as though the tax price does not exist if it is not included in the shelf price, resulting in higher demand than a perfectly rational consumer would exhibit. Limited attention and cognitive costs related to mental effort are at the root of this consumer behavior, leading consumers to rely on the information that is given to them rather than all available information. These findings directly tie to our thesis, in which we test these mechanisms in a public transport setting.

Busse, Silva-Risso & Zettelmeyer (2006) bring forth another analysis providing evidence that consumers fail to behave as rational price optimizers.[8] By studying car transactions in the U.S., they show how temporary manufacture promotions, for example, cash-back discounts, are not entirely passed through to the transaction prices for consumers. Instead, dealers absorb part of the promotional value by negotiating other components in the total price paid by the consumer. However, the buyers act as if they are receiving the full discount, leading them to pay more than a rational consumer would.

[7] Chetty et al., "Salience and Taxation."
[8] Busse et al., "$1,000 Cash Back."

Grubb & Osborne (2015) provides further insight into how consumers' beliefs are systematically biased and limited in learning, even in an environment that is repeated or with abundant information. [9] By studying mobile phone plan contract selection, they show that consumers consistently underestimate their future consumption and end up selecting tariff plans that lead to avoidable higher fees. This inaccurate estimation persists despite the monthly feedback consumers receive with their invoice, suggesting a persistence of biased beliefs.

We build on the ideas presented in these three papers by investigating consumer decision-making and whether there is any similar inaccurate estimation exhibited by consumers in the public transport industry. DellaVigna & Malmendier (2006) serves as an anchor for our thesis, both in the sense that we follow a similar structure and that we aim to test similar predictions. [10] In their paper, the authors find that gym members in the U.S. tend to choose a membership contract that is not cost-minimizing as they base their decision on an overestimation of their future attendance. Holders of monthly memberships attend too infrequently for the membership to be worth the price-point compared to lower-priced options, such as a 10-visit pass, leading to unnecessarily high spending. Similarly, we test for systematic overspending to investigate whether consumers exhibit similar failure to cost-minimize in their contractual choices in the public transport industry.

We then take this analysis further to test for potential weather effects on consumer choices and overspending by performing regressions similar to those of Busse et al. (2015).[11] In their paper, the authors show that car buyers' choices are systematically influenced by same-day weather conditions, with warmer temperatures prompting them to purchase convertibles instead of four-wheel drive vehicles. Illustrating the influence of projection bias as buyers fail to look past the temporary present conditions in a decision affecting their future. Similarly, we investigate whether the weather affects which type of ticket a consumer chooses to purchase, and if it also has an effect on the probability of overspending.

The remainder of the thesis is organized as follows: In Section I, we introduce the public transport industry, the main features of the consumer and weather datasets, and our sample construction. In Section II, we discuss our theoretical underpinnings along with our predictions. Section III concludes.

I. Consumer & Weather Datasets

A. The Public Transport Industry

This thesis focuses on the public transport system in the region of Västra Götaland in Sweden. It is located on the west coast and is home to the city of Gothenburg, the second most populous city in the country.[12] Västra Götalandsregionen is the overarching regional public transport authority, responsible for how public transport should be expanded and where investments should be made.[13]

[9] Grubb and Osborne, "Cellular Service Demand."
[10] DellaVigna and Malmendier, "Paying Not to Go to the Gym."
[11] Busse et al., "The Psychological Effect of Weather on Car Purchases."
[12] Statistikmyndigheten SCB, "Folkmängd och befolkningsförändringar - Kvartal 2, 2025."
[13] Västra Götalandsregionen, "Så styrs kollektivtrafiken."

Västtrafik AB (Västtrafik) is a subsidiary of this authority and is responsible for planning and procuring public transport on behalf of Västra Götalandsregionen. Västtrafik decides how routes should be planned, where stops should be located, the scheduling, and whether a route should be discontinued. Politicians in the regional council decide how public transport should be run at a general level.

This thesis specifically focuses on Västtrafik for the following reasons:

Large commuter base – Västtrafik has over 444 000 consumers using their services every day.[14] This provides for a large and diverse population (service workers, students, younger consumers, older consumers, etc.), making findings more generalizable.

Clear single ticket vs. period ticket choice – Västtrafik has clear period ticket options for consumers, as well as flexible single tickets, allowing for a comparison between the two types.

Availability of consumer data – through Västtrafik's To Go app, anonymous data about individuals' purchases of both single and period tickets is easily extractable.

Natural variation in weather – Västra Götaland's strong variation in weather between and within seasons allows for a stronger analysis of potential weather impact on decision-making.

Practical accessibility – as we are based at the Stockholm School of Economics in Sweden, Västtrafik as an option allowed for an easier understanding of the local context and easier communication with the firm.[15]

Transferability to similar systems – the findings from this thesis are transferable to other metropolitan public transport systems that propose a similar single ticket vs. period ticket choice, making Västtrafik a relevant setting for insights that could be extended elsewhere.

B. Public Transport Consumer Data – Västtrafik

Data on consumers of Västtrafik's services was provided by Västtrafik themselves. This panel data spans from January 1st, 2024, to August 31st, 2025, and covers daily individual purchase activity. All the data originates from the Västtrafik To Go app, which connects purchases to an individual person by assigning them a consumer ID, hence, consumer purchases can be traced back to specific individuals. This allows us to analyze the decision-making process at an individual consumer level, rather than dealing with aggregate figures.

C. Weather Data – SMHI

We obtained data for the weather in Gothenburg from the public website for the Swedish Meteorological and Hydrological Institute (SMHI).[16] The data is from the three following weather stations: 1. Göteborg Sol 2. Göteborg A 3. Göteborg-Landvetter Flygplats. The data is updated on a daily basis and goes back multiple decades, allowing for calculations of historical averages while also providing recent values. All variables from SMHI's data

[14] "Västtrafik AB."
[15] We were also in contact with Stockholms Lokaltrafik (SL), responsible for the public transport in the Stockholm region, but determined that they were a much less fitting option for our thesis due to their lack of detailed consumer data.
[16] SMHI, "Ladda ner väderobservationer."

were presented in the raw data with values on an hourly basis per date, except for *Temperature,* which had three data points at times 06:00, 12:00, and 18:00.

D. Sample Construction and Variables of Interest

We base the majority of the analysis on the two datasets previously mentioned: 1. Public Transport Consumer Data (Västtrafik) and 2. Weather Data (SMHI).

When it comes to Västtrafik's consumer data, our sample only includes data for consumers and tickets that fit the following two conditions:

1) *Registered in the App* – Only data from purchases made through the Västtrafik To Go app are included in the sample.
2) *Zone A* – The data has been cut down to include tickets only valid within zone A.

Figure 1: Map of the Three Zones A, B, and C in which Västtrafik Operates[17]



Both filters were decided together with Västtrafik during the acquiring of the data, meaning our raw data already has these two conditions applied. According to the information provided by Västtrafik during our personal communication, the share of consumers who are registered in the app and purchase their tickets there is about 90 percent of the total consumer base. Hence, the requirement of a consumer ID to track consumer behavior does make for such a strong constraint on our experiments, as most observations are still included. We decided to only include zone A in our experiments as individuals traveling within this smaller zone have a wider choice of alternative transport they could use on top of Västtrafik's services (e.g., walking, driving, cycling, etc.), whereas consumers traveling within zones B and C, and between the zones, travel further, and thus, have fewer options. Hence, consumers in zone A are more likely to switch between different modes, facilitating analysis on differences in decision-making and behavior. Moreover, without data on where a ticket is purchased, the large sizes of zones B and C make the connections to the weather data very general, meaning potential effects in our findings would be inaccurate. Weather conditions measured by weather stations in

[17] "Zoner - Västra Götaland."

Gothenburg are likely similar to the conditions in Partille, but less so for far-away locations like Bengtsfors (see figure 1).

The variables we analyze specifically from the consumer data are the following: a) *Purchase Date* – The date the ticket was purchased by the consumer (which is also the date the ticket is activated/used) b) *Price* – The price of the ticket purchased by the consumer c) *Discount Date* – The date a discount was provided for the consumer (if it was provided at all) d) *Consumer ID* – Each person registered in the app has a consumer ID that their purchases are assigned to.

The discount date variable refers to Västtrafik's discount feature for single tickets, where a person purchasing four or more single tickets during a 7-day period get a 20% discount on *all* the tickets purchased within that period. The discount period resets once the seven days are over.

We constructed the sample of data from SMHI manually, combining data on our variables of interest from the three weather stations mentioned previously. The variables analyzed are the following: a) *Temperature* – the air temperature (in °C) b) *Precipitation* – the amount of rain or snowfall (in mm) c) *Cloud cover* – share of the area of the sky covered by clouds (0-8 oktas)[18] d) *Sunshine hours* – amount of time in an hour the sun shines (in hours, from 0 to 1).

We processed the data for all weather variables as to have one average value for each variable per date. The average is calculated including only values recorded between 06:00 and 18:00 for all variables, including the values for those two specific times. Hence, the values for the weather variables used for the remainder of the thesis are these average values. The sample covers data from January 1st, 2024, to August 31st, 2025, for both datasets.[19]

[18] Cloud cover can also take on a value of 9 oktas, which indicates that the cloud cover could not be accurately determined due to fog, heavy snow, or other obstructions. This is only the case for around 1% of observations.

[19] In addition to the two datasets, we manually collected data on public holidays & school holidays. Public holidays are defined as bank holidays in Sweden and were taken from a calendar. School holidays were measured as holiday for school children in Gothenburg – using a conservative approach to account for different durations of holidays.

Table 1 – Definitions of all dependent and independent variables

Variable	Definition
Independent	
Purchase date	The date a ticket was purchased (to assign purchases to specific time periods).
Price	The price of the ticket purchased (to calculate amount spent on ticket types during a period and identify consumer categories).
Discount date	The date a discount was awarded for the tickets purchased in the previous 7 days
Consumer ID	A specific customer ID attributed to everyone registered in Västtrafik's app (to associate each purchase to a specific and anonymous individual).
Public Holiday	Dummy variable equaling 1 if there is a bank holiday.
School Holiday	Dummy variable equaling 1 if it is a school holiday in Gothenburg.
Weather variables	
Temperature anomaly	The difference between the average temperature of day t (between 6am and 6pm) and the 30-year average temperature (between 6am and 6pm) in degrees Celsius.
Precipitation	Average precipitation in mm for a day t.
Cloud cover	The fraction of cloudiness on day t in oktas.
Sunshine hours	The number of sunshine hours for a day t.
Weather_{t-k}	Weather is a combined vector of the above weather variables and t-k signals the lag of the weather variable. We test for k=1 and k=2.
Season	Which season it is, we use spring and early summer measuring from March to July.
Season*Weather	The interaction effect of season on weather.
Dependent	
Overspending	The net difference of cumulative single ticket cost for a fixed period less the flat fee ticket for that same period, given cumulative single ticket cost is greater than the flat fee.
Period ticket purchase	If a consumer bought a period ticket or not.
Single ticket purchase	If a consumer bought a single ticket or not.

E. Ideal Data & Methodology

In an ideal experiment, we would have access to more detailed datasets. On the consumer side, information such as home and work locations, typical commute routes, specific location and time of ticket purchase, access to alternative modes of transport, and other socio-demographic characteristics (e.g., age, income, household size, etc.) would allow us to control for potential individual-specific determinants of consumption more accurately. These variables would offer clearer insight into whether the consumer behavior we observe is due to expectation errors or simply individual differences we are unable to capture. In the absence of these controls, weather effects ought to be evaluated as correlations and not definitive causal effects. Moreover, increased precision in the weather data would further enhance connections between the conditions and consumer behavior. With a higher number of weather stations providing detailed conditions for precise areas, and measurements on a minute instead of hourly basis, each ticket purchase could be matched with the precise weather conditions that the specific consumer

experienced at that time and place, rather than relying on the aggregate weather conditions in the area for the whole day.

Methodologically, the ideal design would involve a more experimental framework, instead of an observational approach, capable of isolating specific effects. For example, random variation in weather forecasts, controlled information shocks, and eliciting certain beliefs among consumers (e.g., control the announced weather forecasts), could be used directly to measure consumer expectations in a more controlled environment and then compare them to the observed realized behavior. Such an experiment is run in Bertrand, Karlan, Shafir & Zinman (2010),[20] in which the authors analyze a direct mail field experiment implemented by a South African consumer lender who randomized advertising content, loan prices, and offer deadlines, allowing them to find how specific factors affect demand. A similar experiment would allow us to find similar specific relationships between certain weather conditions and demand for different ticket types, and for effects on overspending.

Additionally, a longer sample period spanning multiple years would strengthen the analysis of seasonal effects and consumer learning. It would allow us to follow individual consumers and study how they may adapt to weather over time, such as some cyclists perhaps becoming more resistant to rain or cold. It would also provide for a more accurate analysis of seasonal differences with data on multiple sample periods for every season of the year, compared to our sample period, which does not even include two periods for every season. Together, these data and experimental improvements would allow for the identification of a more causal impact of weather on ticket choices and overspending.

F. Contractual Menu

Västtrafik offer many different types of tickets, especially different combinations of zones their services operate in.[21] Since we are focusing on travel solely within zone A, we only consider tickets providing valid transport within this specific zone. There is a total of three consumer categories that each person fits into: 1) *Adult*, 2) *Student*, for ages 20 and above, and 3) *Youth*, for ages 1 to 19.

Table 2 illustrates the contractual menu that all Västtrafik's consumers are faced with when looking to use their services. Any choice made to start using public transport or switching between ticket types is made in relation to this contractual menu. Note that students are excluded as a consumer category from this thesis, as they are indistinguishable from the Adult and Youth categories, since we use the purchase price of each transaction as an indication of which category the consumer belongs to, and the prices are the same as these categories for Single, Day, and 3-Day tickets, and 30-Day and 90-Day tickets, respectively. Moreover, our analysis focuses on the comparisons between single tickets and 30-Day tickets (and 90-Day tickets in prediction and finding 2).

[20] Bertrand et al., "What's Advertising Content Worth?"
[21] Such as combination tickets for zones A and B or zones A, B, and C, etc.

Table 2 – Västtrafik's Menu of Contracts for Zone A[22]

Ticket Type	*Consumer Category*		
	Adult	**Youth**	**Student***
Single Ticket (90 min)	37 SEK	28 SEK	37 SEK
Day Ticket	120 SEK	90 SEK	120 SEK
3-Day Ticket	240 SEK	180 SEK	240 SEK
30-Day Ticket	860 SEK	645 SEK	645 SEK
90-Day Ticket	2320 SEK	1740 SEK	1740 SEK

Notes: The 90-Day Youth Ticket has a "Leisure" option available for purchase for consumers ages 7-19 for only 925 SEK. This ticket is only valid 14:00-04:00 on weekdays and around the clock on weekends, public holidays, and other holidays. This leisure ticket is excluded from our data. The prices in the table are as of the 2025-09-26 price calendar.

G. Descriptive Statistics

Table 3 shows the allocation of ticket transactions between the different ticket types and customer categories, as well as the quarterly means of all four weather variables. The differences in average price per ticket are due to price increases that Västtrafik put in place within our sample period.

Single tickets constitute the lion's share of transactions, with roughly 1 million and 80 thousand transactions per month, for Adults and Youths, respectively. Conversely, monthly passes transactions vary between 30 to 40 thousand (10-14 thousand for Youths) transactions per month. The quarterly revenue from the two types is similar. SEK 97–114 million for single tickets and SEK 87–111 for 30-day tickets.

[22] Authors' data collection from Västtrafik's To Go app (September 2025).

Table 3: Descriptive Statistics by Ticket Type, Age Group and Quarter

	2024				2025		
Metric	**2024 Q1**	**2024 Q2**	**2024 Q3**	**2024 Q4**	**2025 Q1**	**2025 Q2**	**2025 Q3**
90-Day Pass - Adult							
Number of Transactions	11,183	5,825	9,925	8,474	11,758	6,096	7,309
Total Revenue (SEK)	25,107,203	13,124,100	22,345,246	19,075,045	27,128,110	14,129,728	16,940,176
Average Price per Ticket (SEK)	2247.66	2255.00	2255.00	2255.00	2309.37	2320.00	2320.00
90-Day Pass - Youth							
Number of Transactions	6,558	2,582	6,454	4,360	7,268	2,753	3,827
Total Revenue (SEK)	11,026,258	4,359,862	10,880,896	7,361,302	12,579,198	4,783,956	6,645,756
Average Price per Ticket (SEK)	1684.02	1690.00	1690.00	1690.00	1732.63	1740.00	1740.00
Monthly Pass - Adult							
Number of Transactions	116,891	103,737	90,217	113,020	129,642	111,850	57,311
Total Revenue (SEK)	97,249,475	86,513,014	75,193,754	94,249,623	111,114,236	96,076,276	49,207,996
Average Price per Ticket (SEK)	833.16	835.00	835.00	835.00	858.05	860.00	860.00
Monthly Pass - Youth							
Number of Transactions	35,669	31,116	27,878	36,497	40,859	34,313	16,611
Total Revenue (SEK)	22,217,583	19,423,000	17,384,375	22,783,875	26,261,355	22,105,956	10,690,101
Average Price per Ticket (SEK)	623.82	625.00	625.00	625.00	643.45	645.00	645.00
Other							
Number of Transactions	19,834	29,362	31,938	27,793	21,143	32,906	26,157
Total Revenue (SEK)	2,607,898	3,847,244	4,300,326	3,655,544	2,876,307	4,569,186	3,757,548
Average Price per Ticket (SEK)	132.90	132.48	135.81	132.85	137.36	140.05	144.74
Single Ticket - Adult							
Number of Transactions	2,768,613	2,975,674	2,686,242	3,051,961	2,802,494	3,113,115	1,853,156
Total Revenue (SEK)	97,250,386	106,228,375	97,244,244	108,452,030	101,633,033	114,816,668	69,963,226
Average Price per Ticket (SEK)	35.94	36.00	36.00	36.00	36.95	37.00	37.00
Single Ticket - Youth							
Number of Transactions	219,520	246,160	261,984	249,103	221,601	273,574	198,709
Total Revenue (SEK)	6,135,681	7,025,756	7,571,637	7,042,351	6,387,496	8,110,609	6,026,966
Average Price per Ticket (SEK)	26.90	27.00	27.00	27.00	27.91	28.00	28.00

Notes: Ticket prices are sometimes not integers due to the price changes introduced in Q1 2024 & 2025. Other tickets include 24-hour & 72-hour tickets, both for Youth and Adults, thus accounting for the varying average ticket prices. 2025 Q3 only includes July and August data, hence explains the significantly lower number of transactions. Single ticket revenue is not adjusted for discounts.

Table 4 presents the summary statistics for the ticket quantities of three different ticket types purchased, the spending on single tickets, and the four weather variables. The maximum values for the ticket quantities are many standard deviations from the mean values, suggesting they are rare outliers. Purchasing multiple period tickets within a month, 30-day or 90-day, seems like an irrational waste of money, considering the tickets are activated immediately after purchase, meaning their periods of validity overlap. Although it could be that the consumer refunded one ticket only to buy a new one shortly after.

A similar case is observed for single tickets with a high maximum of 125 tickets, which leads to the maximum spending and overspending in the table. The low mean monthly overspending of SEK 3.20 on single tickets per adult consumer suggests that overspending behavior is rare and has a small impact overall on the group of consumers.

Table 4: Summary Statistics for Ticket Quantities, Spending, and Weather

Variable	Mean	SD	Min	Max	N
Ticket quantities (customer-month, Adults)					
30-day passes per customer-month	0.18	0.39	0.0	5.00	3903686
90-day passes per customer-month	0.02	0.12	0.0	3.00	3903686
Single tickets per customer-month	4.99	6.20	0.0	125.00	3903686
Spending & overspending (SEK / customer-month, Adults)					
Discount received (SEK / customer-month)	11.25	35.80	0.0	813.60	3161739
Overspending amount (SEK / customer-month)	3.20	33.72	0.0	3089.00	3161739
Spending after discount (SEK / customer-month)	210.15	206.79	35.0	3924.00	3161739
Spending before discount (SEK / customer-month)	221.39	234.15	35.0	4068.00	3161739
Weather (daily values, sample period)					
Cloudiness index (daily)	2.70	2.66	0.0	9.00	548
Precipitation (mm, per SMHI observation)	0.10	0.28	0.0	3.51	544
Sunshine (hours/day)	0.39	0.36	0.0	1.00	548
Temperature anomaly (°C, daily)	1.36	3.26	-10.4	8.32	548

As for the weather variables, the high standard deviation and range of temperature anomaly indicate how the temperatures in our sample period vary largely from their 30-year average, in both colder and warmer directions, although the mean value of 1.36°C suggests higher daily temperatures on average. Notably, precipitation has four missing values, which are accounted for in all our regressions.

II. Contract Choice

A. Theoretical Underpinnings

As we aim to determine how rational consumers are in their decision-making, the actions a perfectly rational individual undertakes serve as a benchmark for comparison. The *rational model* showcases how a fully rational individual should behave, based on three fundamental assumptions: (1) *Perfect foresight & expectations* – the individual is aware of exactly how often they will use public transport in a given period. [23]

(2) *Utility maximization* – the individual chooses from the menu of contracts to maximize their utility subject to any budget constraints. Maximizing utility is synonymous with minimizing costs in this thesis. Camerer, Issacharoff, Loewenstein, O'Donoghue & Rabin (2003)[24] express utility maximization in mathematical terms as the following equation:

$$\max_{c_t, C_t} U_t = u(c_t) + \beta E_t[u(c_{t+1})] \quad (1)$$

where c_t denotes the present consumption, C_t is the contract picked, $\beta \in (0, 1)$ measures the intertemporal discount factor ($\beta \approx 1$ implies time preference is of low importance), and E_t is the current information-based expectations at time t.

(3) *No bias* – the individual does not over- or underestimate their motivation for public transport usage. If the rational model were to hold, consumers would not overspend on single tickets in a month; they would instead carefully evaluate their future consumption of that month and choose the contract that would minimize their cost, no matter what that

[23] Tirole, "The Theory of Industrial Organization."
[24] Camerer et al., "Regulation for Conservatives."

contract is. Resulting in a general decision rule that perfectly rational consumers follow without mistake:

- *If the individual expects to use public transport often enough that a period pass costs less per use than single tickets:* they purchase a period ticket.

$$P \times E_t[Q_t] > F \rightarrow Choose\ period\ ticket \quad (2)$$

- *If the individual expects to use public transport rarely enough that single tickets cost less per use than a period ticket:* they purchase single tickets.

$$P \times E_t[Q_t] \leq F \rightarrow Choose\ single\ tickets \quad (3)$$

From equations (2) and (3), we can then define the break-even point where a consumer ought to buy a period ticket: $Q_B = F / P$. If a consumer expects to travel more than Q_B times, they should buy a period ticket. Conversely, if the consumer expects to travel less than Q_B, they would be better off buying single tickets.

If a consumer deviates from these conditions, it implies the failure of a consumer's foresight and/or that their expectations about future travel are biased. An explanation for such a deviation from the rational model is found in projection bias.[25] It is the tendency for an individual to assume that their future needs, wants, or tastes will be more similar to their present situation than they actually will be. Essentially, it leads to an underestimation of expected changes in the future and decision-making in the present, as if their temporary current self would persist longer than it does. Camerer et al. (2003)[26] mathematically derived projection bias as follows:

$$E_t[Q_{t+1}] = (1 - \lambda)E_t^*[Q_{t+1}] + \lambda s_t \quad (4)$$

where $\lambda \in (0, 1)$ is the degree of projection bias (higher λ means greater projection bias), s_t is the present state of the consumer, and $E_t^*[Q_{t+1}]$ is the unbiased expectation of future public transport needs.

Similarly to projection bias, salience can distort the future expectations of a consumer. Salience refers to how present experiences can receive different amounts of attention, and under projection bias, how the weighting of these experiences potentially skews future expectations.[27] Relating this to weather, different weather conditions will produce varying salience levels and consequently induce projection bias to different degrees. Weather conditions with a noticeable physical effect are of high salience (precipitation and temperature deviations), conversely, weather conditions with minimal physical effect will are of low salience (cloud cover and sunshine hours). High-salience conditions translate into a stronger influence of S_t under equation 4, thus more projection bias, which ultimately can skew consumer contract choices.

To illustrate in practical terms how a consumer chooses from a menu of contracts, we consider an individual who perfectly follows the rational benchmark. Due to their rational

[25] Camerer et al., "Regulation for Conservatives."
[26] *Ibid*.
[27] Bordalo et al., "Salience and Asset Prices."

nature, they successfully select the cost-minimizing contract thanks to their perfectly accurate expectation of future travel frequency. Conversely, a consumer subject to projection bias may have their expectations distorted by temporary salient conditions, and the wants and needs they experience because of them, leading to a potential over- or underestimation of future travel frequency. This can, in turn, lead to a failure in selecting the cost-minimizing contract, as this decision is made on an inaccurate estimation, leading to unnecessarily high costs, i.e., overspending. This is even though they too are looking to minimize their cost.

B. Predictions of Consumer Decision-Making

Under this benchmark, it follows that we should be able to observe overspending occurring on the individual level, i.e., $P \times Q_t > F$. In other words, some travelers will fail to meet the criteria of cost minimizing under the rational model, such that $P \times Q_t \leq F$ – indicating that the consumer either suffers from a behavioral bias or lacks perfect foresight of future public transport usage. If the individual is subject to projection bias, short-term conditions can distort their expectations $E_t[Q_t+1]$, leading to a potential under- or overestimation of subsequent public transport consumption.

In the following sections, we investigate this framework through a set of empirical predictions that we compare to the rational benchmark. Section B.1. investigates the existence of systematic overspending, while sections B.2. through B.4. investigate the effect of weather on ticket purchases and overspending. This approach allows us to benchmark behavior against theoretical predictions and helps us uncover the mechanisms behind potential deviations.

B.1. Predictions 1 & 2: Observed Overspending

In predictions 1 & 2, we first consider the choice consumers have between purchasing a single ticket at each use of public transport, with price P and quantity Q (number of tickets), or opting to purchase a period ticket, for a flat fee F. We look at whether there is any overspending and what the magnitude of this overspending is. Formally, overspending is defined as:

$$Overspending_{i,t} = max\{0, P \times Q_{i,t} - F_t\} \quad (5)$$

Where $Q_{i,t}$ is the trips by individual i realized over a period t[28]

Prediction 1 (rationality in decision-making): *The majority of consumers who buy single tickets should accumulate a total cost for those single tickets less than or equal to the 30-day flat fee. Overspending will exist but be minuscule in prevalence.*

Prediction 2 (sustained rationality in decision-making): *The vast majority of consumers who buy single tickets should accumulate a total cost for those single tickets less than or equal to the 90-day flat fee. Overspending should be even less common than for a 30-day period.*

[28] We use the max-operator to make sure overspending is only recorded when the cumulative single ticket cost exceeds the flat fee.

Prediction 1 & 2 Reasoning – According to the rational benchmark, individuals make decisions that minimize their expected costs. Formally, an individual would select the contract where their expected travel frequency satisfies either:

$$\mathrm{P} \times E_{30}[Q_{i,30}] \lesseqgtr F_{30} \tag{6}$$

Or:

$$\mathrm{P} \times E_{90}[Q_{i,90}] \lesseqgtr F_{90} \tag{7}$$

P is the price of a single ticket and Q_{30} (Q_{90}) is the corresponding number of single tickets purchased for one 30-day (90-day/roughly a quarter) period. P includes the discount effect of a consumer purchasing 4 or more tickets during distinct occasions in a week. F_{30} (F_{90}) is the flat fee for a 30-day (90-day) ticket.

It follows that rational consumers of single tickets, during a 30-day period, would travel less than or equal to the break-even point $Q_B = F / P$. On the other hand, those expecting $E_t[Q_t] > Q_B$ will opt for the flat-rate ticket. Overspending occurs when an individual deviates from this framework and fails in cost minimizing, which entails that the perfect foresight (1) and/or no bias assumption (3) is violated. Furthermore, extending the period to 90 days reveals critical insight about overspenders: if individuals learn from prior false expectations, we should not observe overspending over longer periods of time.[29]

Finding 1 (rationality in decision-making): *For the majority of the sample, individuals follow the rational formula in Prediction 1, spending a total amount on single tickets less than the price of a 30-day during a 30-day period. However, there is an overall overspending rate of 1.8 % for Adults (2.7% for strategic switchers) and 0.5% for Youths.*[30]

Table 5 shows the mean spending, standard deviation, and number of observations for consumers in the two groups: $P \times Q > F$ (overspenders) and $P \times Q \leq F$. This is then translated into an overspending rate illustrating the share of the total number of observations that are overspenders.

[29] Worth noting is that there might be other constraints than lack of learning, leading to overspending, such as liquidity or risk-aversion with regards to not sufficiently utilizing a period ticket. We can't distinguish between these different factors and thus acknowledge that they might exist. At the same time, these problems should partially be solved by strategic switchers who at least have demonstrated prior liquidity (and risk-aversion).

[30] The inability to classify a ticket as belonging to the Student category results in a conservative approach in the results since purchases of single tickets by students are compared to the higher flat fee for Adults, and not the student flat fee. This underestimates the amount of overspending and the overspending rate for Adults.

Table 5: Monthly Spending Patterns WITH WEEKLY DISCOUNTS (SEK)

Period	$P \times Q > F_{30}$			$P \times Q \leq F_{30}$			Overspending Rate	Avg Discount (SEK)	Total N
	Mean	SD	N	Mean	SD	N	Overspend Rate	Avg Discount (SEK)	Total N
2024-01	1024.4	(175.0)	4646	202.7	(187.4)	149998	0.030	13.6	154644
2024-02	987.4	(142.8)	2453	198.3	(180.2)	141173	0.017	12.6	143626
2024-03	993.3	(172.8)	2027	190.6	(174.0)	141293	0.014	10.8	143320
2024-04	1037.6	(194.5)	5231	208.1	(188.8)	163446	0.031	12.6	168677
2024-05	1003.9	(182.0)	2214	190.4	(172.0)	161197	0.014	10.7	163411
2024-06	990.9	(162.7)	1550	180.9	(162.1)	159914	0.010	9.5	161464
2024-07	1053.2	(209.1)	2096	177.1	(159.1)	159723	0.013	8.9	161819
2024-08	1005.5	(171.2)	1759	182.2	(163.5)	161506	0.011	10.4	163265
2024-09	1038.5	(192.6)	5265	199.5	(183.5)	164044	0.031	12.2	169309
2024-10	996.9	(159.2)	2156	188.1	(172.5)	153945	0.014	10.4	156101
2024-11	992.7	(151.3)	2374	193.1	(176.8)	155756	0.015	11.6	158130
2024-12	1033.2	(190.5)	4135	204.2	(181.4)	182488	0.022	11.4	186623
2025-01	998.1	(151.3)	2915	197.6	(180.2)	146460	0.020	12.3	149375
2025-02	995.9	(157.3)	2429	190.6	(174.9)	148544	0.016	10.6	150973
2025-03	1048.9	(200.6)	5901	202.6	(184.6)	164211	0.035	12.1	170112
2025-04	999.7	(162.1)	1878	184.1	(166.4)	163185	0.011	8.9	165063
2025-05	1000.7	(161.5)	2579	190.3	(172.3)	174639	0.015	10.1	177218
2025-06	1038.0	(191.8)	4394	194.8	(174.7)	196059	0.022	10.1	200453
2025-07	1022.9	(183.5)	1125	161.6	(145.0)	158108	0.007	6.5	159233
2025-08	984.1	(146.4)	1572	176.4	(158.8)	173299	0.009	7.9	174871
Overall Adult	1019.4	(180.1)	58699	190.7	(173.5)	3218988	0.018	10.6	3277687
Overall Youth	783.1	(250.8)	2093	87.9	(90.3)	410630	0.005	3.2	412723

*Notes: P*Q > F represents individuals (adults) overspending, i.e. the cumulative cost of single tickets in a month is greater than the flat fee. P*Q < F represents the individuals (adults) that are not overspending. Mean shows the average cumulative cost of a customer for the respective classifications – standard deviation is in parentheses. N represents the total number of individuals for that category. Overspending rate is calculated as N(overspending)/N(Total) and shows the proportion of individuals overspending in a month.*

We see that there is an overall overspending rate of 1.8% for Adults, with those individuals spending an average of 1012.3 SEK, and 0.5% for Youths, with an average spending of 783.1 SEK. Moreover, the overspending fluctuates significantly in relative terms, ranging from 1%-3.5% during the sample period. Due to the low amount of overspending from the Youth category, we choose to exclude this category from closer analysis in the next table.

Table 6: Strategic Switchers (Adults): Monthly Spending Patterns WITH WEEKLY DISCOUNTS (SEK)

Period	$P \times Q > F$			$P \times Q \leq F$			Overspending Rate	Avg Discount (SEK)	Total N
Year Month	Mean	SD	N	Mean	SD	N	Overspend Rate	Avg Discount	Total N
2024-01	1036.5	(178.9)	1764	203.0	(194.2)	41707	0.041	18.3	43471
2024-02	992.5	(154.6)	974	216.4	(193.3)	32059	0.029	19.4	33033
2024-03	991.0	(157.8)	864	216.3	(190.6)	33431	0.025	17.4	34295
2024-04	1041.6	(202.3)	2222	237.3	(207.0)	38926	0.054	21.1	41148
2024-05	999.6	(165.3)	1037	226.1	(192.4)	39866	0.025	18.3	40903
2024-06	984.1	(171.7)	846	217.9	(181.1)	45162	0.018	16.2	46008
2024-07	1039.7	(197.5)	1053	208.7	(174.6)	48352	0.021	14.3	49405
2024-08	991.0	(154.1)	928	215.7	(182.8)	44923	0.020	17.2	45851
2024-09	1041.3	(192.6)	2302	232.0	(201.4)	42332	0.052	20.3	44634
2024-10	997.7	(158.2)	1026	219.5	(191.9)	38191	0.026	18.0	39217
2024-11	988.3	(150.2)	1008	218.4	(193.3)	37716	0.026	18.6	38724
2024-12	1005.6	(169.8)	1296	226.0	(192.0)	46771	0.027	17.8	48067
2025-01	1020.2	(147.7)	829	225.5	(199.8)	35966	0.023	18.7	36795
2025-02	1022.3	(152.8)	741	212.3	(191.4)	36801	0.020	16.1	37542
2025-03	1077.2	(203.9)	1736	229.8	(204.3)	39580	0.042	18.9	41316
2025-04	1013.4	(150.0)	684	214.2	(186.4)	41782	0.016	13.8	42466
2025-05	1022.7	(144.0)	857	224.3	(194.7)	42413	0.020	16.1	43270
2025-06	1064.5	(189.6)	1719	234.9	(197.8)	52273	0.032	17.9	53992
2025-07	1025.5	(181.2)	395	184.1	(158.5)	45992	0.009	10.8	46387
2025-08	1015.1	(147.7)	634	207.8	(180.3)	46894	0.013	14.8	47528
Overall	1025.1	(177.9)	22915	218.4	(190.6)	831137	0.027	17.1	854052

*Notes: P*Q > F represents individuals overspending, i.e. the cumulative cost of single tickets (after adjusting for discounts) in a month is greater than the flat fee. P*Q < represents the individuals that are not overspending. Mean shows the average cumulative cost of a customer for the respective classifications – standard deviation is in parentheses. N represents the total number of individuals for that category. Overspending rate is calculated as N(overspending)/N(Total) and shows the proportion of individuals overspending in a month. Youths are omitted from the sample because of their negligible size – most evidently Youth tickets are subsidized by the local authorities.*[31]

In table 6 we consider "strategic switchers", that is, individuals who at some point during the sample period have bought a 30-day ticket. The point of this is to exclude consumers who are infrequent travelers and only buy tickets sporadically. The assumption behind this is that someone who purchases a 30-day ticket at some point travels a decent amount, or at least enough not to be considered a sporadic user of public transport. In this case, the overspending rate is 2.7% for adults, meaning 2.7% of strategic switchers suboptimally select single tickets - nearly a 1% increase in percentage points.

Finding 2 (sustained rationality in decision-making): *For the majority of the sample, individuals follow the rational formula in Prediction 2, spending a total amount on single tickets less than the price of a 90-day ticket during a 90-day period. However, there is still an overall overspending rate of 1.0% for Adults (1.2% for strategic switchers) and 0.2% for Youths.*

Table 7: Quarterly Spending Patterns WITH WEEKLY DISCOUNTS (SEK)

Period	$P \times Q > F_{90}$			$P \times Q \leq F_{90}$			Overspending Rate	Avg Discount (SEK)	Total N
	Mean	SD	N	Mean	SD	N	Overspend Rate	Avg Discount (SEK)	Total N
2024 Q1 Adult	2681.5	(415.3)	2765	391.7	(448.2)	222451	0.012	24.3	225,216
2024 Q1 Youth	2003.4	(336.0)	57	134.3	(188.3)	35753	0.002	4.7	35,810
2024 Q2 Adult	2697.8	(454.8)	2584	389.0	(434.3)	246358	0.010	21.7	248,942
2024 Q2 Youth	2073.4	(409.6)	66	134.0	(184.2)	39917	0.002	4.6	39,983
2024 Q3 Adult	2724.7	(479.0)	1903	367.2	(407.8)	257905	0.007	20.0	259,808
2024 Q3 Youth	2074.0	(597.0)	76	132.0	(181.0)	44801	0.002	5.5	44,877
2024 Q4 Adult	2696.5	(423.3)	2654	387.0	(436.6)	253003	0.010	21.8	255,657
2024 Q4 Youth	2007.6	(367.5)	79	134.8	(190.8)	41335	0.002	5.0	41,414
2025 Q1 Adult	2789.4	(459.5)	3202	392.5	(453.9)	237232	0.013	22.9	240,434
2025 Q1 Youth	2057.8	(291.1)	89	142.2	(202.9)	35057	0.003	5.3	35,146
2025 Q2 Adult	2755.7	(438.9)	2297	376.9	(426.5)	276367	0.008	19.0	278,664
2025 Q2 Youth	2020.3	(229.6)	75	137.5	(186.5)	45765	0.002	4.4	45,840
2025 Q3 Adult	2598.9	(262.3)	60	252.1	(267.9)	232736	0.000	10.4	232,796
2025 Q3 Youth	3193.1	(1846.2)	5	112.1	(140.8)	34893	0.000	3.6	34,898

*Notes: P*Q > F represents individuals overspending, i.e. the cumulative cost of single tickets in over three month is greater than the flat fee. P*Q < represents the individuals that are not overspending. Mean shows the average cumulative cost of a customer for the respective classifications – standard deviation is in parentheses. N represents total amount of individuals for that category. Overspending rate is calculated as N(overspending)/N(Total) and shows the proportion of individuals overspending in a month.*

Table 7 reports the same information as table 5, but over a quarterly (90-day) period. Individuals who spent more in total on single tickets during those 90 days than the price of a 90-day ticket are considered to be overspenders. The overspending rate shows systematic overspending, although it remains very low overall, with 1.0% for Adults and 0.18% for Youths (excluding Q3 2025 for fair measurement).[32]

[31] "Skolkort i grundskolan."
[32] Calculated as total N of overspenders divided by total N for respective category (weighted)

Table 8: Strategic Switchers (Adults): Quarterly Spending Patterns WITH WEEKLY DISCOUNTS (SEK)

Period	$P \times Q > F_{90}$			$P \times Q \leq F_{90}$			Overspend Rate	Avg Discount (SEK)	Total N
Period	Mean	SD	N	Mean	SD	N	Overspend Rate	Avg Discount	Total N
Quarter_1	2744.9	(431.2)	858	415.4	(464.0)	57602	0.015	34.8	58460
Quarter_2	2739.6	(454.8)	1058	476.8	(484.8)	61603	0.017	37.7	62661
Quarter_3	2704.3	(395.5)	616	444.2	(442.3)	67706	0.009	32.7	68322
Quarter_4	2733.1	(412.7)	987	456.7	(478.2)	62551	0.016	38.1	63538
Quarter_5	2734.9	(459.0)	807	428.3	(463.8)	59607	0.013	32.1	60414
Quarter_6	2717.0	(420.7)	931	465.4	(478.2)	67123	0.014	32.7	68054
Overall	2729.3	(430.3)	5304	431.3	(452.8)	441653	0.012	32.7	446957

*Notes: P*Q > F represents individuals overspending, i.e. the cumulative cost of single tickets (after adjusting for discounts) over three months is greater than the flat fee. P*Q < represents the individuals that are not overspending. Mean shows the average cumulative cost of a customer for the respective classifications – standard deviation is in parentheses. N represents the total number of individuals for that category. Overspending rate is calculated as N(overspending)/N(Total) and shows the proportion of individuals overspending in a month. Youths are omitted from the sample because of their negligible size – most evidently Youth tickets are subsidized by the local authorities.*[33]

As in finding 1, by adjusting for strategic switchers, we observe a higher overspending rate of 1.2% in table 8, compared to 1.0% in table 7.

Findings 1 & 2 Interpretation – Under the decision rules in equations (2) and (3), a cost-minimizing consumer should purchase a period ticket (30- or 90-day) if their expected usage satisfies $P \times E_t[Q_t] > F$; if not, they purchase single tickets per trip. Thus, systematic overspending should not occur, since the expectations are perfectly accurate and unbiased.

However, from both predictions 1 & 2, we see a low but systematic and non-trivial overspending on public transport, suggesting breach of perfect foresight and/or no bias. A consumer lacking perfect foresight risks building inaccurate expectations of their future travel frequency, while a bias-suffering consumer is influenced by exogenous variables that could impede their expectation's accuracy. These external variables could be related to changes in household income, age, or weather, as seen in Busse et al. (2015) and later discussed in this thesis.[34] Ultimately, these factors risk translating into tangible overspending on single tickets. Furthermore, a downwards shift in $E_t[Q_{i,t+1}]$ built by projecting the present temporary conditions into the future, indicates suffering from projection bias.

Notably, even under longer time spans, some travelers still fail to cost-minimize under equations (2) and (3). This indicates that, on one hand, there is some learning behavior, as the overspending rate is considerably lower for the 90-day ticket than for the 30-day ticket. On the other hand, it suggests that learning may not be instant, as a considerable number of consumers keep overspending. Considering this, biases can be rendered not to be pure noise, but rather systematic. Our findings mirror the findings of DellaVigna & Malmendier (2006) and suggest systematic bounded rationality.[35]

[33] "Skolkort i grundskolan."
[34] Busse et al., "The Psychological Effect of Weather on Car Purchases."
[35] DellaVigna and Malmendier, "Paying Not to Go to the Gym."

Evaluating the strategic switchers, their higher overspending behavior is hard to explain by the mere absence of information.[36] It conversely points towards that they violate the assumption of perfect foresight, as they fail to accurately predict their future usage $E_t[Q_{t+1}]$ – or that their expectations are distorted by contemporaneous events like seasonally good weather, implying breach of the no bias assumption. Clearly, lack of information alone cannot explain the systematic overspending of consumers.

Our results in findings 1 & 2 provide evidence that the assumption of consumer rationality made in neoclassical literature is not necessarily accurate. While many consumers seem to align with the rational benchmark, the observed overspending suggests this is not the case for everyone.[37] This indicates that the neoclassical assumption of rational behavior of consumers is an approximation, as some consumers may behave optimally, while a subset systematically deviates from the rational cost-minimizing benchmark.

Finding and interpretation 1 & 2 – Welfare loss

The evident conclusion from findings 1 & 2 is that despite the discount system in Västtrafik, some consumers still overspend, which results in a welfare loss. It is defined as the cumulative amount overspent on single tickets for an arbitrary period, i.e., the difference between the sum of single ticket expenses (less discounts) and the flat fee F for that same period, given the sum of single ticket expenses > F. On the individual level, this amount might seem negligible.

Table 9: Welfare Loss from Non-Optimal Ticket Choice (Single-Ticket Users)

	2024				2025		
Metric	**2024 Q1**	**2024 Q2**	**2024 Q3**	**2024 Q4**	**2025 Q1**	**2025 Q2**	**2025 Q3**
Avg. Loss (SEK, overspenders) — Mean (SD)	169.96 (167.63)	184.84 (188.93)	197.87 (200.42)	175.11 (173.03)	186.30 (181.31)	181.23 (178.66)	164.12 (203.60)
% Overspending (users)	2.87	2.68	2.80	2.47	3.27	2.33	1.04
Avg. Loss (All Users, SEK)	3.34	3.23	3.55	2.92	4.28	2.86	1.32
Total Welfare Loss (SEK)	1,590,175	1,710,369	1,881,734	1,574,436	2,163,459	1,664,769	469,725
Avg. Discount Effect (SEK)	11.83	10.57	10.28	10.75	11.24	9.43	7.15
Quarterly N (unique users)	243,431	268,066	279,945	275,814	258,985	300,192	249,081

Notes: Avg. Loss for overspenders displays the average total overspending for a quarter – mean to the left and standard deviation in parentheses. % overspending (users) shows the share of customers overspending for the whole quarter. N represents the total number of unique *individuals for that* quarter. *Total welfare loss is the total amount overspent for the whole quarter. 2025 Q3 only includes values from July and August.*

As shown in table 9, the average loss for an overspending individual (over a quarter) is varying between a mere SEK 170 – 200. However, the aggregate quarterly welfare loss of around SEK 1.75 million and an annual loss exceeding SEK 7 million (omitting the incomplete quarter of Q3) demonstrate more substantial figures. From a holistic perspective, this means forgone utility induced by inaccurate expectations. For Västtrafik, this results in additional revenue, which poses the question of whether the public transport system is set up in a way that unintentionally induces overspending behavior. They could implement a more user-friendly 'capping' system where single tickets are free for a consumer once their total monthly spending reaches the price of a flat-rate ticket. While their discount feature may reduce overspending, such a mechanism could protect their consumers from it completely.

[36] It should be noted that they most likely possess sufficient knowledge on prices to make a monetary evaluation of which option cost minimizes under the rational benchmark.
[37] Tirole, "The Theory of Industrial Organization."

However, the discount could still protect consumers from potential overspending and also be behind the relatively low welfare loss. Some customers who are eligible for the discount would have, if the discount had not been implemented, reached a cumulative single ticket cost greater than the flat fee ticket, thus they would have overspent. In table 10, we see what the annual amount consumers would have spent extra on single tickets if there were no rebate function in place, i.e., consumers' annual savings thanks to the rebate.[38]

Table 10: Consumer Spending and Welfare Loss if There Were No Rebate

Scenario	Share_infra	Annual_raw_discount_SEK	Annual_effective_loss_SEK
100% of trips unaffected (upper bound)	1.00	20930901	20930901
90% unaffected	0.90	20930901	18837811
75% unaffected	0.75	20930901	15698176
50% unaffected	0.50	20930901	10465450
25% unaffected	0.25	20930901	5232725

Notes: Table 10 displays the total annual effective cost of the discount system on single tickets for Västtrafik. Share_infra is a number between 0 and 1 that shows the potential share of discounts trip taken. This means that under a 0.50 share_infra, only 50% of the trips (that reached discount eligibility) would have been pursued.

Assuming the quantity of single ticket purchases is completely unaffected by the inexistence of a rebate, we can formulate the savings as follows:

$$Savings^{annual} = \sum_{i,t} (Cost_{it}^{no\ discount} - Cost_{it}^{rebate}) \quad (8)$$

$$where\ Cost_{it}^{no\ discount} = PQ_{it}\ and\ Cost_{it}^{rebate} = PQ_{it} - discount \times PQ_{it}$$ [39]

We see that, holding that share_infra = 1, consumers would spend over SEK 20 million more annually on single tickets (had there not been a rebate). Even if only 25% of the trips were unaffected, it would still result in SEK 5 million more in annual spending, from which we can draw an assumption that at least some consumers would be overspending if it were not for the rebate.[40] On the flip side, the discount is a source of missed revenue for Västtrafik and rather protects consumers from overspending on their services.

While the results in table 10 suggest that the rebate has a positive impact on consumer welfare, this may not necessarily be the case. It could be that consumers aware of the rebate are more tolerant of the risk of overspending when buying more single tickets, as they feel a sense of protection. In other words, some consumers could be inclined to purchase higher quantities of single tickets because they know they can earn a discount

[38] The existence of the discount could have prompted consumers to purchase more single tickets due to a feeling of safety, which is why we include different percentages of unaffected trips.
[39] Annual savings are synonymous with the annual discount but reflect a different perspective of equation (8).
[40] We recognize that consumers who are rational would, without a rebate system in place, adjust their decisions in accordance with the changed decision rule for optimal ticket choice, following according to the rational equation. Without the rebate, the quantity threshold becomes lower for choosing a single ticket, and consequently, more consumers, if they are rational, would buy the flat fee ticket. Intuitively, some people under a rebate system would fall short of the quantity threshold for a flat fee ticket to be worth it, but conversely, without rebate be above the threshold and buy a flat fee ticket. Since the rebate system increases that quantity threshold, it offers more flexibility for consumers, but without it, we at least expect some consumers to miscalculate their future usage and then overspend.

on them and be shielded from overspending. Some consumers of period tickets could also be inclined to switch to purchasing single tickets, as the rebate may drop the price of their expected consumption of single tickets below the flat-fee ticket price.

This comfort in purchasing higher quantities of single tickets may actually lead to a higher total spending, despite the 20% discount, compared to if there were no rebate. However, this assumes that these tickets were not planned before (for example, under a flat fee ticket), hence it is difficult to conclude if this truly would be the case or not.

This would be the case if consumers end up purchasing tickets they otherwise would not have purchased, had it not been for the rebate, at a total price higher than the savings from the discount.[41] In which case, the rebate, counterintuitively, reduces consumer welfare. A similar idea is illustrated in Heimer, Iliewa, Imas & Weber (2021), where it is found that overconfidence increases for consumers when they feel shielded from the full consequences of their decisions, making individuals more prone to future repeated, suboptimal choices.[42] Hence, the rebate could have the opposite effect of saving consumers' money, and actually encourage riskier behavior, leading to less cost-efficient behavior.

B.2. Predictions 3 & 4: Weather Impact on Ticket Purchases

In predictions 1 & 2, we observed contractual choices and overspending behavior by consumers of Västtrafik's services; in predictions 3 & 4, we analyze how weather impacts these purchasing decisions. More specifically, prediction 3 looks at how same-day weather conditions affect period ticket purchases, while prediction 4 analyzes a lagged effect of weather on the purchases of both ticket types.

Prediction 3 (immediate weather impact): *According to assumption 3 (no bias) of the rational model, temporary weather conditions on the date of purchase have no impact on the purchase quantity of 30-day flat fee tickets. Hence, we predict that contemporary weather conditions should not systematically influence period ticket sales.*

$$\begin{aligned}\text{log_tickets}_{it} = {} & \alpha_i + \beta_1 \times weather_{it} + \beta_2 \times public_holiday_t \\ & + \beta_3 \times school_holiday_t + \gamma_m + \varepsilon_t \end{aligned} \quad (9)$$

$$\begin{aligned}\text{log_tickets}_{it} = {} & \alpha_i + \beta_1 \times weather_{it} + \beta_2 \times public_holiday_t \\ & + \beta_3 \times school_holiday_t + \gamma_m + \delta_w + \varepsilon_t \end{aligned} \quad (10)$$

$Log_tickets_{it}$ is the logarithmic version of period ticket sales for a transaction i on a given day t which harmonizes the interpretation and variance of the variable. The variable $weather_{it}$ is a vector combined of precipitation in mm, sunshine in hours, cloudiness in oktas (fraction covering the sky), and temperature anomaly in degrees Celsius capturing contemporaneous weather conditions. $Public_holiday_t$ and $school_holiday_t$ are dummies controlling for bank holidays and school holidays respectively. γ_m is monthly time fixed effects and δ_w weekly time fixed effects.[43]

[41] $Q_t^{rebate} > Q_t^{no\ rebate}$ *in such a way that* $PQ_t^{rebate} \times (1 - discount) > PQ_t^{no\ rebate}$
[42] Heimer et al., "Dynamic Inconsistency in Risky Choice."
[43] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.

Prediction 4 (lagged weather impact on ticket purchases): *The weather conditions leading up to the date of purchase of rational consumers should have no impact on the purchase quantity of 30-day flat fee tickets or single tickets.*

$$\log(\text{periodtickets})_{it} = \beta_0 + \beta_1 weather_{it} + \beta_2 weather_{it-1} + \beta_3 weather_{it-2} + \beta_4 public_holiday_t + \beta_5 school_holiday_t + \gamma_s + \delta_w + \varepsilon_t \quad (11)$$

$$\log(singletickets)_{it} = \beta_0 + \beta_1 weather_{it} + \beta_2 weather_{it-1} + \beta_3 weather_{it-2} + \beta_4 public_holiday_t + \beta_5 school_holiday_t + \gamma_s + \delta_w + \varepsilon_t \quad (12)$$

$Log(periodtickets)_{it}$ and $log(singletickets)_{it}$ is the logarithmic version of period- and single ticket sales for a transaction i on a given day t - which harmonizes the variance and interpretation of the variable. The variable $weather_{it}$ is a vector combined of precipitation (mm), sunshine hours, cloud cover (oktas, fraction of the sky) capturing contemporaneous conditions, and temperature anomaly in degrees Celsius. $Weather_{it-1}$ and $weather_{it-2}$ are the same vectors but lagged t-1 and t-2 days.[44] $Public_holiday_t$ and $school_holiday_t$ are dummies controlling for bank holidays and school holidays respectively. γ_m is monthly time fixed effects and δ_w weekly time fixed effects.[45]

Prediction 3 & 4 Reasoning – Under the rational benchmark, decision-making remains unaffected by temporary weather conditions outside of their own expectations of future consumption.[46] However, for individuals suffering from projection bias, exogenous, and especially salient conditions like days with high precipitation or abnormally warm temperature may prompt inaccurate estimations of future travel frequency. In prediction 3, we examine whether this phenomenon is occurring contemporaneously. We then extend the test for one- and two-day lagged effects to see whether consumers form expectations and make decisions based on recent past weather on top of same-day conditions.

Finding 3 (immediate weather impact on period ticket purchases): *There is a 1.4% decrease in period ticket purchases for each degree Celsius in temperature anomaly. The insignificance of precipitation, sunshine hours, and cloud cover indicates that not all aspects of weather necessarily systematically trigger a specific purchasing decision.*

Table 11 reports the results of equations (9) and (10) OLS regression of temperature anomaly, precipitation, sunshine hours, cloud cover, public holiday, and school holidays on the daily period tickets bought, with weekly and monthly time-fixed effects.[47] From the month- + weekday fixed-effects model we find that temperature anomaly is significant with a coefficient of -0.014.

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[44] Stock, *Introduction to Econometrics*.
[45] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.
[46] Tirole, "The Theory of Industrial Organization."
[47] *Temperature Anomaly* – This variable is an indicator of how the daily temperature deviates. For a specific date, it is calculated by subtracting the 30-year average temperature, between 06:00 and 18:00, for that specific date, from the date's *Temperature* value.

Table 11: Prediction 3 – Weather effects on daily period ticket sales

	Dependent variable: log(Period tickets)	
Variable	Time FE (month)	Time + Weekday FE
Temperature anomaly (°C)	-0.014 (0.008).	-0.014 (0.006)*
Precipitation (mm)	-0.073 (0.085)	-0.096 (0.064)
Sunshine hours	-0.040 (0.101)	-0.082 (0.076)
Cloud cover (oktas)	0.005 (0.013)	0.002 (0.010)
Public holiday (dummy)	-0.440 (0.115)***	-0.390 (0.087)***
School holiday (dummy)	-0.167 (0.066)*	-0.101 (0.050)*
Observations	602	602
R^2 / Adj. R^2	0.322 / 0.292	0.625 / 0.605

Note:
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{.}p < 0.10$

Notes: The table shows values of coefficients and regular OLS standard errors (in parentheses) for the time-fixed effects OLS (logarithmic) model showing the effect of weather on the sale of daily period tickets. Temperature anomaly is measured in degrees Celsius, precipitation in mm of rain, sunshine in hour, and cloud cover as a fraction of coverage on the sky (oktas). All variables are logarithmic to stabilize variance and for harmonized interpretation. Public- and school holidays are dummies that equals 1 if there is a bank- respective school holiday and equals 0 if not. Time-fixed effects are run with monthly & weekly dummies to control for temporal effects.[48]

This shows that on a given date, there is a decrease of 1.4% in 30-day flat fee ticket sales, ceteris paribus, for each degree Celsius the temperature is above that date's 30-year average. Precipitation, sunshine hours, and cloud cover are all insignificant and thus seem not to influence period ticket sales.

Finding 3 Interpretation – The significant effect from temperature anomaly shows a modest influence of weather on period ticket sales. Taken together with the insignificance of the other variables, it suggests that the weather influence on period ticket sales is minor, with only some indication of consumer reaction to salient weather conditions.

A likely reason for the temperature anomaly as the standalone effect may be its more salient nature. This means that temperature deviations are more noticeable for individuals, while the other three variables are perhaps more transient and short-lived. In this case, it follows that they would not have a similar impact as a temperature anomaly. In practice, positive temperature deviation affects feasibility of public transport substitutes, making it appear as more pleasant to for example, walk or bike.

Alternatively, insignificance may suggest that while there may be a reaction to these weather variables, it is not systematic across all individuals but rather heterogenous, which could cancel out their effect on 30-day ticket purchases on an aggregate level. Thus, while the temperature anomaly finding seems to provide support for prediction 3 and demonstrate a modest form of projection bias, the other insignificant variables indicate that not all aspects of weather systematically trigger a specific decision with regard to same-day 30-day ticket purchases.

[48] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.

Finding 3 – Robustness check

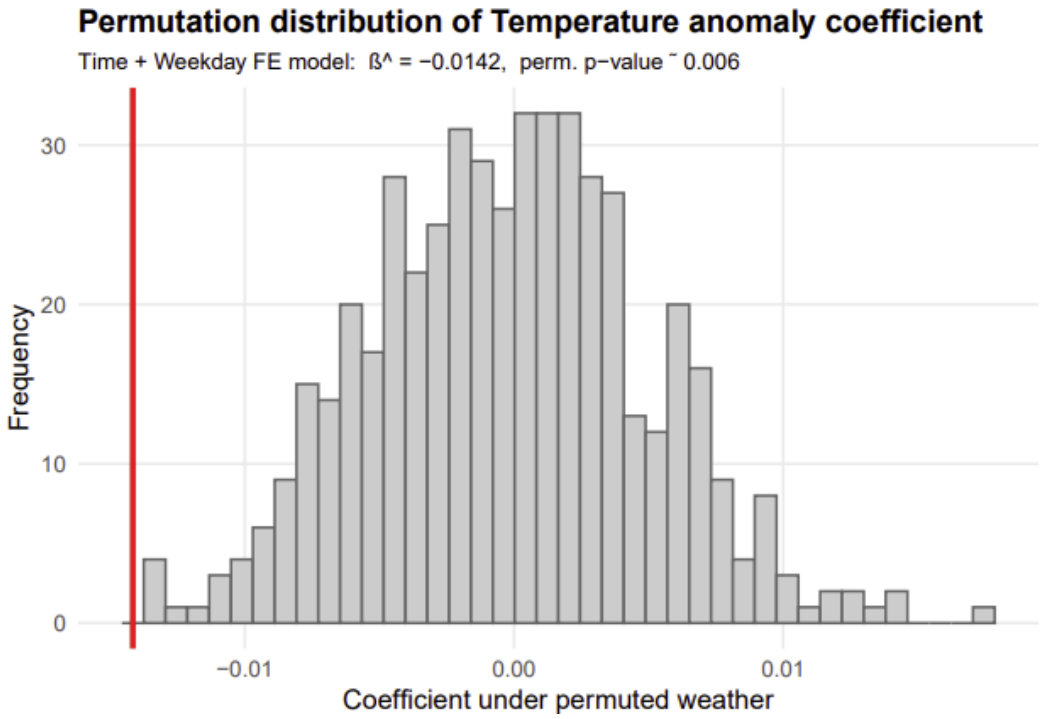
Table 12: Prediction 3 – Permutation Test Summary for Weather Effects on Period Tickets

	Time FE (month)			Time + Weekday FE		
Variable	Estimate (Time FE)	Model p (Time FE)	Perm p (Time FE)	Estimate (Time + WD FE)	Model p (Time + WD FE)	Perm p (Time + WD FE)
Temperature anomaly (°C)	-0.0140 **	0.124	0.038	-0.0142 ***	0.099	0.006
Precipitation (mm)	-0.0727	0.218	0.396	-0.0960	0.056	0.140
Sunshine hours	-0.0400	0.712	0.678	-0.0816	0.367	0.220
Cloud cover (oktas)	0.0053	0.751	0.644	0.0015	0.914	0.836

Note:
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (stars based on permutation p-values; 500 random weather reassignments).

Notes: The table displays the results of a permutations test on prediction 3's OLS model for period tickets – iterated 500 times. Significant values indicate that the coefficients earlier in the prediction OLS are unlikely to be random. "Estimate" shows the coefficients that were priorly yielded from the prediction OLS, "Model p-value" shows the p-values from the OLS prediction ran on equation (9) and (10), and "Permutation p-value" shows the p-values from the permutations test.[49] Temperature (t) is measured in degrees Celsius, precipitation (t) in mm of rain, cloud cover as a fraction of coverage on the sky (oktas), and sunshine in hours.

In table 12, the results of the permutations test confirm the earlier findings in table 11, with all prior insignificant coefficients falling under the null in the permutations test, and temperature anomaly maintains its predictive power in the weekday time-fixed effects model, meaning that it is improbable that it arose by random chance.[50]



Notes: Figure 2 displays the random distribution from the permutations test iterated 500 times for temperature anomaly's effect on period ticket sales under the weekly time-fixed effects model. The red line indicates where the coefficient from the original regression lies relative the randomly generated coefficients.[51]

As seen in figure 2, it becomes clear that temperature anomaly belongs to the extreme values of the permutations test as highlighted by the red line. If this was not the case, the red line would be inside the bulk of the bell curve (and not in the tail). This graph can be

[49] Fisher, "The Design Of Experiments."
[50] The permutations shed confidence on our results because it reflects the result of the coefficients had there not been any effect of weather at all. Thus the distribution shows the empirical null.
[51] Young, "Channeling Fisher."

generated for each coefficient in a permutations test, but by virtue of vastness constraints, we choose to only include this example. The other graphs would be analogous to this one.

Finding 4 (lagged weather impact on ticket purchases): *There seems to be a positive lagged effect of two days of 14.7% for precipitation on the purchases of period tickets – temperature anomaly remains its significance from prediction 3. The rest of the coefficients are insignificant, suggesting, as seen in finding 3, that not all aspects of weather necessarily systematically trigger a specific purchasing decision.*

Table 13 reports the results from the daily fixed-effects models from equations (11) and (12) examines how short-term weather fluctuations influence ticket purchasing behavior. The specification controls for unobserved, time-invariant differences between ticket categories (30-day vs. single tickets) and includes seasonality adjustments, as well as public holiday indicators. Standard errors are Newey-West with a 7-day lag to correct for serial correlation. The lagged effects are daily, where t–1 indicates a difference of one day.

Table 13: Prediction 4 – Daily Lagged Weather Effects on Ticket Sales

	Dependent variable: log(Tickets)	
Variable	Period	Single
Weather variables		
Temperature anomaly (t)	-0.020 (0.010)*	-0.003 (0.003)
Temperature anomaly (t−1)	0.003 (0.013)	-0.001 (0.004)
Temperature anomaly (t−2)	0.010 (0.010)	0.001 (0.003)
Sunshine hours (same day)	0.118 (0.085)	0.026 (0.026)
Sunshine hours (t−1)	0.010 (0.071)	-0.019 (0.022)
Sunshine hours (t−2)	0.029 (0.069)	-0.011 (0.022)
Cloud cover (oktas)	0.009 (0.010)	-0.001 (0.003)
Precipitation (same day, mm)	-0.044 (0.073)	-0.027 (0.023)
Precipitation (t−1, mm)	0.079 (0.073)	-0.007 (0.023)
Precipitation (t−2, mm)	0.147 (0.073)*	0.001 (0.023)
Seasonality controls		
Seasonality (sin)	0.036 (0.029)	0.003 (0.009)
Seasonality (cos)	0.185 (0.038)***	-0.030 (0.012)*
Model statistics		
Observations	607	607
R^2 (Adj.)	0.488 (0.471)	0.702 (0.692)

Note:
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: The table shows values of coefficients and Newey-West HAC standard errors with a 7-day lag (in parentheses) for the time-fixed effects OLS (logarithmic) model showing the lagged effect of weather on the sale of daily period- and single tickets. [52,53] *Temperature anomaly is measured in degrees Celsius, precipitation in mm of rain, cloud cover as a fraction of coverage on the sky (oktas), and sunshine in hours. Period- and single ticket variables are logarithmic to stabilize variance and for harmonized interpretation. Public- and school holidays are dummies that equals 1 if there is a bank- respective school holiday and equals 0 if not. Time-fixed effects are run with weekly dummies in order to control for temporal effects.*[54] *The sine and cosine variables control for seasonality in the data.*[55] *Cloud cover lagged is omitted from the regression due to low added independent variation and the inflation of multicollinearity when*

[52] Newey and West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix."
[53] Stock, *Introduction to Econometrics*.
[54] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.
[55] Harvey, *Forecasting, Structural Time Series Models and the Kalman Filter*.

including them. This also makes sense because lagged cloud cover should be, at least partially, captured by sunshine hours and precipitation.

We see that through both models, lagged precipitation is significant in predicting period tickets. The positive coefficient with magnitude 0.147 suggests an increase in period ticket purchases, all else equal, of 14.7% on a given day for each millimeter of precipitation two days prior to the day of purchase.

All other predictors are insignificant across both models, implying that all short-term weather conditions except precipitation and temperature deviation are unable to explain variations in ticket sales. In other words, consumer expectations remain unaffected by these contemporaneous conditions.

Findings 4 Interpretation – In finding 3, the significant same-day negative effect of temperature anomaly on period ticket purchases (also found in prediction 4) suggests consumers respond to an immediate weather shock. Similarly, the positive 2 day lagged effect of precipitation on period ticket purchases suggests a reaction to weather shocks leading up to the moment of purchase. This deviation from the rational benchmark implies that consumer expectations are distorted by exogenous factors, though only limited to certain specific weather conditions. It follows that these consumers (who shift expectations based on short-term weather shocks) violate assumption 3 (no bias) of the rational model, in the form of a weather-induced projection bias. Notably, both precipitation and temperature represent high-salience weather conditions with considerable physical impact. Thus, more salient weather conditions seem to more clearly influence ticket sales.

Similar results were found in Busse et al. (2015), where temperature was shown to be of the highest behavioral salience among the other weather conditions.[56] Different from their paper, however, which solely focuses on same-day effects, our insights from finding 4 suggest there may be lagged weather-induced projection bias originating from precipitation. The positive coefficient of the lagged precipitation variable suggests projection bias can originate in a more dynamic form, operating over multiple days.

For the weather conditions that do not systematically influence ticket sales, the results align with our predictions and further resonate with the rational benchmark, since these conditions do not seem to induce projection bias and consequently do not violate any of the rational assumptions.

As single tickets only have insignificant predictors, it can be concluded that consumers of these tickets do not systematically factor in weather fluctuations in their consumption. This largely makes sense as they should not need to forecast future travel frequency when confronted with a contractual decision. Therefore, temporary weather shocks don't disturb future expectations. It could also be because certain consumers purchase single tickets so sporadically that they do not even consider any other options. For them, purchasing a single ticket may not be synonymous with declining the option to purchase a 30-day ticket, as they may not even consider it as another option because of their low use of public transport. Hence, future conditions or expectations are completely irrelevant to them, and the weather conditions cannot influence them. Conversely, period tickets require clearer forecasting, in which weather conditions might distort the perceived need

[56] Busse et al., "The Psychological Effect of Weather on Car Purchases."

of future travel, and thus why we observe significant results for high-salience weather variables.

It is important to note that these results relate to decisions whether to purchase specific ticket types or not, not actual overspending. Hence, while the effect observed from the significant weather variables suggests some bounded rationality, as consumers seem to be influenced by external factors, this bounded rationality does not necessarily lead to a lack of rationality in terms of overspending. An individual opting out of purchasing a period ticket because of abnormally warm temperatures does not necessarily mean they will purchase a number of single tickets high enough in the future that would lead to overspending.

Finding 4 – Robustness check

Table 14: Prediction 4 – Permutations Test Summary for Daily Lagged Weather

	Period tickets			Single tickets		
Variable	Estimate (Period)	Model p (Period)	Perm p (Period)	Estimate (Single)	Model p (Single)	Perm p (Single)
Temperature (t)	-0.0204 ***	0.046	0.000	-0.0029 *	0.290	0.098
Temperature (t−1)	0.0027	0.723	0.644	-0.0008	0.772	0.682
Temperature (t−2)	0.0101 *	0.251	0.094	0.0006	0.818	0.762
Sunshine (t)	0.1176 *	0.250	0.084	0.0263	0.387	0.234
Sunshine (t−1)	0.0096	0.869	0.854	-0.0191	0.299	0.260
Sunshine (t−2)	0.0291	0.664	0.632	-0.0108	0.627	0.510
Cloud cover (t)	0.0090	0.593	0.348	-0.0006	0.890	0.822
Precipitation (t)	-0.0439	0.507	0.558	-0.0268	0.139	0.220
Precipitation (t−1)	0.0787	0.262	0.318	-0.0071	0.694	0.752
Precipitation (t−2)	0.1469 **	0.015	0.048	0.0007	0.969	0.974

Note:
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (stars based on permutation p-values).

Notes: The table displays the results of a permutations test on prediction 4's OLS model for period- & single tickets – iterated 500 times.[57] Significant values indicate that the coefficients earlier in the prediction OLS are unlikely to be random.[58] "Estimate" shows the coefficients that were priorly yielded from the prediction OLS, "model p" shows the p-values from the OLS prediction ran on equation (11) and (12), and "perm p" shows the p-values from the permutations test. Temperature (t) is measured in degrees Celsius, precipitation (t) in mm of rain, cloud cover as a fraction of coverage on the sky (oktas), and sunshine in hours. Cloud cover lagged is omitted from the regression due to low added independent variation and the inflation of multicollinearity when including them. This also makes sense because lagged cloud cover should be, at least partially captured by sunshine hours and precipitation.

From the permutation test in table 14, we can see that, firstly, the significance of our variables lagged precipitation and temperature anomaly, regressed on period tickets, is likely not to be a result of random chance (p-value = 0.048 and 0.000, respectively, from the permutations test), thus upholding our earlier interpretations and demonstrating robust results. Secondly, temperature (anomaly) (t-2) and sunshine (t) changed from insignificant to relatively significant, meaning they are extreme values of the random null distribution, and thus not just pure statistical noise. However, their sizes continue to be minor and hence do not change our prior interpretations. Thirdly, the p-values from the single tickets demonstrate that these coefficients all fall inside the null distribution, implying that there is no systematic correlation between lagged weather and single ticket sales.

B.3. Prediction 5: Seasonality of Weather Impact

[57] Fisher, "The Design Of Experiments."
[58] Young, "Channeling Fisher."

From findings 1 & 2, we found that a considerable number of individuals still overspend on single tickets despite Västtrafik's single ticket discount system. Later, in findings 3 & 4, we showed that some elements of weather correlate with period ticket purchases. The question then becomes whether this effect is more pronounced during specific seasons. For example, do sunshine hours have a larger effect on single ticket sales during spring/early summer than their general yearly effect? With the rationale being that people are more optimistic about future weather conditions during this time of year, that could then prompt consumers to opt for alternative modes of transportation, such as biking.

Prediction 5 (season of weather effect): *If prevalent, the effect of weather-induced projection bias is more pronounced in the spring and early summer, when expectations of future weather conditions are more optimistic, compared to the whole sample period.*

$$\log(\text{periodtickets})_{it} = \beta_0 + \beta_1 weather_{it} + \beta_2 weather_{it} \times season_t + \beta_3 public_holiday_t + \beta_4 school_holiday_t + \gamma_s + \delta_w + \varepsilon_t \quad (13)$$

$$\log(\text{singletickets})_{it} = \beta_0 + \beta_1 weather_{it} + \beta_2 weather_{it} \times season_t + \beta_3 public_holiday_t + \beta_4 school_holiday_t + \gamma_s + \delta_w + \varepsilon_t \quad (14)$$

$Log(periodtickets)_{it}$ and $log(singletickets)_{it}$ is the logarithmic version of period- and single ticket sales for a transaction i on a given day t - which harmonizes the interpretation and variance of the variable. The variable $weather_{it}$ is a vector combined of precipitation in mm, sunshine in hours, cloudiness in oktas (fraction covering the sky), and temperature anomaly in degrees Celsius. $Weather_{it} \times season_t$ is the moderating effect of seasons on the same weather vector – the goal is to gauge if there is an amplified effect of weather depending on the concurrent season. [59,60] *$Public_holiday_t$ and $school_holiday_t$ are dummies controlling for bank holidays and school holidays respectively. γ_m is monthly time fixed effects and δ_w weekly time fixed effects.*[61]

Prediction 5 Reasoning – Prediction 5 suggests that the impact weather has on consumer decision-making, observed in findings 3 & 4, may vary or be amplified depending on the season when the purchase takes place. The rational model posits that there should not be any seasonal effect on contract choices after factoring in future travel usage.[62] In other words, a rational consumer would be unaffected by weather optimism/pessimism and strictly base their contract choice on expected consumption $E_t[Q_t+1]$. If the traveler is subject to projection bias, improved weather in the spring and early summer may build on already optimistic thoughts an individual has about future improved weather, which would prompt them to be more reluctant to purchase a period ticket and, in turn, potentially lead to overspending on single tickets. We can therefore gauge with prediction 5 if consumers violate assumption 3 (no bias) by observing if the effect of weather on

[59] Aiken and West, *Multiple Regression*.
[60] Stock, *Introduction to Econometrics*.
[61] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.
[62] Tirole, "The Theory of Industrial Organization."

consumer purchasing behavior is amplified during specific seasons – potentially also indicating that the consumer is in breach of assumption 1 (perfect foresight).

Finding 5 (season of weather effect): *In the spring/early summer, each hour of sunshine increases purchases of single tickets by 12.4%, while overall one hour of sunshine indicates a decrease of 6.8% in single ticket sales. Precipitation reduces single ticket sales by 3.9% per mm of rain (though the effect is invalidated in the permutations test). All weather variables are insignificant in predicting period ticket sales.*

Table 15 illustrates how the impact of the weather on the sales of tickets differs overall compared to in the spring/early summer.

Table 15: Prediction 5 – Weather and Seasonal Moderation Effects on Ticket Sales

Variable	Single tickets	Period tickets
Temperature		
Temperature anomaly	-0.002 (0.003)	-0.018 (0.014)
Temp × Spring	-0.005 (0.006)	0.016 (0.021)
Sunshine		
Sunshine hours	-0.068 (0.034)*	-0.029 (0.150)
Sun × Spring	0.124 (0.055)*	0.151 (0.225)
Precipitation		
Precipitation	-0.039 (0.018)*	-0.059 (0.067)
Precipitation × Spring	0.007 (0.043)	-0.065 (0.133)
Cloud Cover		
Cloud cover	-0.004 (0.004)	-0.020 (0.019)
Cloud × Spring	0.003 (0.009)	0.051 (0.032)
Season & Holidays		
Spring/Early-summer (Mar–Jul)	-0.134 (0.066)*	-0.734 (0.239)**
Public holiday	-0.335 (0.098)***	-0.182 (0.133)
School holiday	-0.124 (0.023)***	-0.373 (0.085)***
Seasonality (sin)	0.040 (0.024).	0.288 (0.090)**
Seasonality (cos)	-0.071 (0.027)**	-0.084 (0.094)
Num.Obs.	602	602
R^2 / Adj. R^2	0.714 / 0.705	0.519 / 0.503
Std.Errors	Newey–West (lag 7)	Newey–West (lag 7)

Note:
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.10$

Notes: The table shows values of coefficients and Newey-West HAC standard errors with 7-day lags (in parentheses) for a time-fixed effects OLS (logarithmic) model showing the moderated effect of seasons on weather on the sale of daily period- and single tickets (including lagged effect). [63] *These are employed to account for serial correlation in the data. Temperature anomaly is measured in degrees Celsius, precipitation in mm of rain, cloud cover as a fraction of coverage on the sky (oktas) and sunshine in hours. Spring (and summer) dummies capture the period of March to July. Spring*weather measures the interaction term of the season on the weather variables. The dependent variable is logarithmic to stabilize variance and for harmonized interpretation. Public- and school holidays are dummies that equal 1 if there is a bank- respective school holiday and 0 if not. Time-fixed effects are run with weekly dummies in order to control for temporal effects. The sine and cosine variables control for seasonality.*

We find that sunshine hours and seasonally moderated sunshine hours correlates with singe ticket sales – having coefficients of -0.068 and 0.124, respectively. This means that a one-hour increase in sunshine hours (sunshine hours during early spring/summer), ceteris paribus, decreases (increases) single ticket sales with 6.8% (12.4%). Moreover,

[63] Newey and West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix."

precipitation is significant for single tickets with a coefficient of -0.039 – meaning a 1 mm increase in rain, all else equal, decreases single ticket sales by 3.9%. The other predictors are insignificant (or only weakly significant), implying no strong correlation between these weather conditions and ticket sales during early spring/summer. For period tickets, the variables are insignificant and suggest no behavioral significance in weather influence on period ticket sales.

Finding 5 Interpretation – In the single ticket regression, we see that sunshine- and seasonally moderated sunshine hours predicted single ticket sales, though with opposite signs pointing towards a season-dependent behavioral mechanism. Through the full year, sunshine hours decrease single ticket sales. This reflects increased feasibility for public transport substitutes such as biking or walking, thus reduced ticket demand, which then aligns with the rational model. However, in spring and early summer, sunshine hours correlate with more single tickets being purchased. This does not necessarily mean that people violate the rational model induced by projection bias, instead it can reflect increased travel overall for leisurely activities. Hence, the effect of sunshine shows consistency with the rational model and is not proof of projection bias. By virtue of data limitation, we cannot isolate the data to only commuting trips, meaning that even if the effect were to reflect weather-driven projection bias, other travelers appreciating the sunny weather would offset and distort this effect by buying single tickets. Lastly, period ticket sales remain unaffected by sunshine hours in the model. Intuitively, this makes sense as a short-term increase in sunshine hours should not have a huge impact on future travel needs. In other words, this is in line with the rational model.

For precipitation, the same-day effect is negatively correlated with the sale of single tickets. This most likely reflects decreased demand for discretionary trips, i.e. leisure travel or miscellaneous consumption done with a degree of spontaneity. Under the rational model, this makes sense since a rational consumer would likely opt-out from spontaneous and optional trips when the weather makes them less feasible. Importantly, precipitation has high salience and thus is expected to at least decently alter general mobility – ultimately not reflecting distortion of expectations but shift in demand. While it seems counterintuitive from the perspective of commotional trips, after all precipitation should increase single tickets because of increased substitution of biking/walking. These trips appear to be outweighed by the decreased discretionary trips, creating a net negative effect, and explaining the negative sign of precipitation. Furthermore seasonally moderated precipitation is insignificant in predicting single ticket sales. Conclusively, precipitation is not more pronounced during spring and early summer.

Notably, the insignificant same-day coefficient for temperature anomaly in finding 5 appears to contradict the significant coefficient for period tickets in finding 3-4. Econometrically, this can be explained by the interaction model including more and multicollinear variables where temperature, sunshine and season-dependent dummies impede model precision – thus low independent variation for the same-day effect remains to be attributed. Simply put, there is a reallocation of explanatory power across the same-day *and* the moderated variables instead of it being concentrated in just one.

Regarding the other predictors (for both models), none has any meaningful significant correlation with ticket sales when seasonally moderated. Therefore, cloud cover and

temperature deviation do not seem to be distorting future expectations after seasonal amplification – aligning with the rational model.

Overall, while there seems to be a differing effect the weather has on the sale of both single- and period tickets depending on the season at hand, there is no coherent evidence pointing to a reliance on single tickets being stronger due to improved weather changes in the spring and early summer. It instead points toward that people either rationally substitute public transport for other transportation modes, or that they increase consumption because of increased leisure activity. Ultimately, there is no consistent evidence of projection bias.

Finding 5 – Robustness check

Table 16: Prediction 5 – Permutation Test Summary for Weather and Seasonal Interactions

	Period tickets			Single tickets		
Variable	Estimate (Period)	Model p (Period)	Perm p (Period)	Estimate (Single)	Model p (Single)	Perm p (Single)
Temperature (t)	-0.0183 **	0.180	0.034	-0.0016	0.623	0.548
Sunshine (t)	-0.0291	0.846	0.812	-0.0680 *	0.043	0.068
Precipitation (t)	-0.0592	0.381	0.546	-0.0392	0.034	0.150
Cloud cover (t)	-0.0203	0.289	0.130	-0.0044	0.309	0.264
Temp × Spring/Early-summer	0.0158	0.443	0.174	-0.0046	0.400	0.196
Sun × Spring/Early-summer	0.1507	0.502	0.384	0.1245 **	0.023	0.012
Precipitation × Spring/Early-summer	-0.0647	0.626	0.652	0.0066	0.877	0.848
Cloud × Spring/Early-summer	0.0515 **	0.111	0.018	0.0026	0.775	0.714

Note:
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$ (stars based on permutation p-values).

Notes: The table displays the results of a permutations test on prediction 5's OLS model for period- & single tickets – iterated 500 times.[64] Significant values indicate that the coefficients earlier in the prediction OLS are unlikely to be random.[65] "Estimate" shows the coefficients that were priorly yielded from the prediction OLS, "model p" shows the p-values from the OLS prediction ran on equation (13) and (14), and "perm p" shows the p-values from the permutations test.

Evaluating the validity of the regression results in prediction 5 using permutations test, we find that all our significant regressors, but precipitation, are extreme values under the distribution of the permutation test. It can therefore be concluded that those results are not occurring because of mere chance. Precipitation, however, is insignificant under the permutations test, implying that the OLS effect was driven by mere chance (since permutations test p-values trumps the original model p-values) and not behavioral correlation. Therefore, the effect of precipitation should be invalidated. Moreover, we see that temperature (t) and sun during spring/early summer turn significant under the permutations test, implying that these coefficients might not be a result of noise and actually could be useful predictors.

B.4. Prediction 6: Weather Impact on Overspending

In findings 1 & 2, we established the existence of systematic overspending among consumers. In findings 3 & 4, we observed how weather impacts contractual choices, which we then analyzed in the spring/early summer compared to the complete sample period in finding 5. It follows that weather conditions affecting contractual choices also could have an effect on overspending, which is what we investigate in prediction 6.

[64] Fisher, "The Design Of Experiments."
[65] Young, "Channeling Fisher."

Prediction 6 (weather impact on overspending): *If specific weather conditions through projection bias affect consumers' contractual choices, and if this causes them to misjudge future consumption, weather may also increase the probability of overspending among consumers who fail to switch optimally between single and 30-day tickets.*

$$\text{is_overspending}_{it} = \beta_0 + \beta_1 weather_{it} + \beta_2 public_holiday_t + \beta_3 school_holiday + \delta_w + \varepsilon_t \quad (15)$$

$Is_overspending_{it}$ is a dichotomous variable deeming if a customer i overspent on single tickets in a specific month t. The variable $weather_{it}$ is a vector combined of precipitation in mm, sunshine in hours, cloudiness in oktas (fraction covering the sky), and temperature anomaly in degrees Celsius. $Weather_{it-1}$ and $weather_{it-2}$ are the same vectors but lagged t-1 and t-2 days. $Public_holiday_t$ and $school_holiday_t$ are dummies controlling for bank holidays and school holidays respectively. δ_w is the individual fixed effects to isolate the within variation of a customer.[66]

Prediction 6 Reasoning – Under the rational benchmark, consumers disregard temporary external factors when they form expectations about future travel needs, implying that, should there be overspending, it should not be affected by the weather. However, as we observe in findings 3 & 4, some weather conditions systematically affect consumers' contractual choices. Since these selections determine spending on single tickets, certain weather conditions could affect overspending – especially high-salience variables like precipitation potentially could increase the probability of overspending.

Finding 6 (weather impact on overspending): *Precipitation positively affects the probability of overspending by 4.0% per millimeter. Temperature anomaly, cloud cover, and sunshine hours have negligible effects.*

Table 17 reports the results of the regression of temperature anomaly, precipitation, sunshine hours, cloud cover, public holidays, school holidays, and seasonality on overspending according to equation (15). In this case, overspending is recorded as a dummy variable with a value of 1 if the individual is overspending, and 0 if they are not. Hence, the impact of the independent variables is to be interpreted as affecting the likelihood of overspending for an individual i.

[66] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.

Table 17: Prediction 6 – Individual-level Fixed-Effects Regression of Overspending on Weather

Variable	Estimate (SE)
Temperature anomaly (°C)	-0.001 (0.000)***
Precipitation (mm)	0.040 (0.002)***
Sunshine hours	0.000 (0.000)***
Cloud cover (0–8 oktas)	-0.002 (0.000)***
Public holiday	0.006 (0.001)***
School holiday	-0.000 (0.000)
Seasonality (sin)	0.006 (0.000)***
Seasonality (cos)	0.017 (0.000)***
Individuals	521498
Observations	3690410
R^2 (Adj.)	0.003 (-0.161)

Notes: The table shows values of coefficients and robust HC1 standard errors (in parentheses) clustered at the individual level using customer_id for individual-level fixed effects OLS (logarithmic) model showing the effect of weather on the probability of overspending (dependent dichotomous variable: is_overspending = 1 if the person overspends that month).[67, 68] *Temperature anomaly is measured in degrees Celsius, precipitation in mm of rain, cloud cover as a fraction of coverage on the sky (oktas), and sunshine in hours. Public- and school holidays are dummies that equals 1 if there is a bank- respective school holiday and equals 0 if not. Individual-fixed effects are run to control isolate within variation for individuals. The sine and cosine variables control for seasonality in the data.*[69] *The negative adjusted R^2 doesn't necessarily invalidate the results of the within variation of a dependent binary variable like "is_overspending". By definition, the formula of adjusted R^2 penalizes our inclusion of multiple regressors – which at the same time also have a minor impact on the explanation of within variation for individuals. The important takeaway is the interpretation and significance of the coefficients in this case.*

We see that the coefficients for all weather variables are statistically significant (but economically irrelevant), suggesting that an individual's overspending behavior on single tickets is related to all four weather conditions we investigate. Precipitation has a coefficient of 0.040, suggesting a 4.0% increase in the probability of overspending, all else equal, per millimeter of rain. Across temperature anomaly, sunshine hours, and cloud cover, we find significance but a mix of generally small effects. While they are all associated with a lower probability of overspending, their small coefficients of -0.001, -0.000, and -0.002, respectively, suggest their effects are negligible, indicating no systematic effect of these three weather conditions on the probability of overspending.

Finding 6 Interpretation – The strongest impact of weather on the probability of overspending being from precipitation adds insight to finding 4, where we observed lagged precipitation increasing perceived future consumption by virtue of projection bias, but the adaptation other tickets differed between consumers. Some travelers quickly adapted to increased travel frequency (indicated by rain), while others delayed this and kept consuming single tickets (despite higher expected travel needs), resulting in

[67] Arellano, "PRACTITIONERS' CORNER."
[68] Wooldridge, *Econometric Analysis of Cross Section and Panel Data*.
[69] Harvey, *Forecasting, Structural Time Series Models and the Kalman Filter*.

overspending. Therefore, it can be concluded that projection bias induced by precipitation may lead to overspending for individuals who fail to adjust their expectations about future travel frequency in time or do so inconsistently. Thus, this suggests bounded rationality under the rational benchmark. Moreover this resonates with prior findings where high-salience variables like precipitation exhibited the most prominent effect on expectations.

Although the other three weather variables are statistically significant, they yield coefficients of small magnitudes, indicating these weather factors have virtually no systematic effect on the probability of overspending. Compared to the rational benchmark, these results suggest that most weather conditions have little or no effect on the financial outcomes of consumer choices. Suggesting an alignment with the rational benchmark for all cases but precipitation. Its observed effect indicates a deviation from the model, implying that certain weather conditions may influence consumers' contractual choices as far as leading to overspending on single tickets and contributing to the welfare loss. Overall, however, the findings suggest that weather is not a substantial predictor of overspending.

Contrasting this to the findings in Busse et al. (2015) reveals a critical difference in how their models are set up differently to ours.[70] Purchasing tickets or a car is an active decision made by an individual at a specific moment, while overspending is an accumulation of decisions aggregated over a month. In the case that contractual choices are affected by weather, they would be diluted when aggregated, meaning these deviations are negligible from an economic perspective. Our model then detects significant but negligible correlations because of the temporal aggregation. Thus, while the model in Busse et al. (2015) also has a low explanatory power, their findings reflect legitimate behavioral differences, since they are not aggregated in any way.

Finding 6 – Robustness check

The extremely small standard errors and very low explanatory power of the model, with an R^2 of 0.003, indicate that the large sample size makes the model detect tiny behavioral differences and finds significant results for all variables. This adds to the conclusion established above that weather is not a substantial predictor of overspending (despite significant coefficients). However, due to how the model is set up – using a plm function in R – running a permutation test, in line with prediction 3-5, to investigate the robustness of the model and the significance of the variables is not plausible.[71]

III. Conclusion

How does the weather affect consumer decision-making? In this thesis, we investigate how consumers of public transport make contractual choices when faced with a menu of ticket choices and whether these choices are systematically affected by weather conditions. Our investigation is based on the following two questions:

[70] Busse et al., "The Psychological Effect of Weather on Car Purchases."
[71] The individual fixed effects model underlying structure could not be feasible kept when running the permutations test causing either the model to omit the fixed effects or make the model unidentifiable.

1. Do consumers of public transport overspend on single tickets, i.e., spend more on them than the price of a period ticket, due to an inaccurate expectation of future consumption?
2. Do weather conditions affect the demand for specific public transport ticket types, and do they affect any potential overspending on single tickets?

By answering these questions, we review the assumption of consumer rationality, made in neoclassical behavioral finance literature, by testing consumer rationality and weather effects in a new setting where we discover how their behavior deviates from and aligns with the rational model benchmark.[72]

We use a panel dataset provided by Västtrafik, covering anonymous consumer purchases made in their "To Go" app – allowing us to observe purchasing behavior on an individual level over a period of around one year and nine months. This dataset alone allows us to observe the quantity of purchases for specific ticket types and identify overspending, which we define as any money spent on single tickets in a given period above the price of a flat-fee ticket for the same period.

Combining this with another panel dataset from the Swedish Hydrological and Meteorological Institute (SMHI), covering the weather conditions surrounding Gothenburg. We run logarithmic OLS- and logistic regressions with individual fixed effects to investigate whether certain weather conditions have an effect on consumers' future expectations and contractual choices, as well as any potential overspending. Essentially, investigating a form of weather-induced projection bias. We also perform robustness tests for each of our findings in the form of permutation tests. While the data we use provides essential insights, access to more individual-specific variables, such as access to alternative modes of transport or household income, would have allowed us to observe weather effects in an isolated experiment to produce more accurate findings.

Nevertheless, we find that a subset of consumers of Västtrafik's services, around 1.8%–2.7% of Adults and around 0.5% of Youths, systematically overspend on single tickets over a 30-day period, compared to the price of a flat-rate ticket. Such behavior indicates a failure to cost-minimize, consistent with deviations related to violations of the rational model's assumptions of perfect foresight and no bias. It follows as a plausible explanation for overspending that these consumers anchor too heavily in their current travel behavior and assume it will continue further into the future than it will in reality, leading to an underestimation of travel frequency in the future. Essentially, a form of bounded rationality caused by distorted expectations from projection bias. A contractual choice based on this underestimation risks leading to overspending if the underestimation prompts a consumer to opt for single tickets instead of a 30-day ticket, even though the flat-fee ticket would have made them better off, because of their high travel frequency.

We also find that certain weather conditions affect contractual choices in ways consistent with projection bias, specifically, abnormally high temperatures seem to have a negative effect on purchases of 30-day tickets, while precipitation two days prior to the purchase seems to raise them. This suggests consumers' expectations of future consumption and the decision-making that goes with it are systematically affected by weather, indicating a form of weather-induced projection bias. However, these are the only same-day and

[72] Tirole, "The Theory of Industrial Organization."

lagged effects we observe, and other than these specific cases, we find that most weather variables have no systematic effect on consumer decision-making. The duality of these results indicates two key findings: Firstly, consumers do not react uniformly to all weather variables; rather it seems that weather has no effect in most cases. Secondly, in the cases where there is an observed effect, the effect originates from either of the two most salient variables: temperature anomaly and precipitation. Suggesting, the weather conditions have to be sufficiently noticeable for consumers' expectations and decision-making to be systematically affected. This applies at least for the overall sample period, as weather conditions during specific seasons do not seem to require the same salience to have an effect on consumers. In the spring/early summer, sunshine hours seem to positively affect purchases of single and 30-day tickets, while this effect is not observed over the whole investigated period.

As for overspending, the positive effect of precipitation – raising the likelihood of overspending by 4.0% – suggests that weather not only has effects on purchases of tickets, but also on consumers' potential overspending. Indicating that weather-induced projection bias not only affects which contracts consumers choose to purchase, it can also lead to an unnecessary financial cost.

Our findings on inaccurate expectations and failure to minimize costs by consumers reinforce the insights found in DellaVigna & Malmendier (2006), as we extend their results from the health club industry to the public transport industry.[73]As we observe similar expectation errors in a different setting, our results indicate that such biases persist across different environments and for different contracts. We take this analysis further as we add to the findings in Busse et al. (2015) by observing similar weather-induced projection bias affecting consumer purchasing decisions in our context as well.[74] Furthermore, we take their findings an extra step by not only investigating general overspending and weather effects on purchasing decisions but also presenting how weather-induced projection bias also has an effect on the overspending we observe. Our findings suggest the existence of bounded rationality, lack of perfect foresight, bias, and deviation from the rational benchmark, indicating that the general assumption of consumer rationality made in neoclassical literature is unlikely to hold universally.

The consumer overspending leads to an annual welfare loss exceeding SEK 7 million, which is synonymous with more revenue for Västtrafik, raising a question of fairness in their pricing design. The lack of a 'capping' mechanism on the purchase of single tickets, where single tickets are free for a consumer once their total monthly spending reaches the price of a flat-rate ticket, suggests Västtrafik allows for consumer overspending. While their discount feature may reduce it, such a mechanism could protect their consumers from it completely. Such an intervention can also be made on a societal level by policymakers or transportation ministers – elaborating on interventions like this act as a natural extension for future research. Our findings also have implications for consumers and their purchasing behavior. If consumers become more aware of potential biases they experience during their decision-making, it may improve their rationality and shorten learning lags in their overspending.

[73] DellaVigna and Malmendier, "Paying Not to Go to the Gym."
[74] Busse et al., "The Psychological Effect of Weather on Car Purchases."

Notably, however, our experiments have some limitations that an ideal experiment would cover. Firstly, while our data covers the basic variables of individual purchases, other individual-specific such as home address, access to alternative modes of transport, or location and exact time of purchase, would have allowed us to control individual-specific variations more accurately, isolate our tests for the effects we are looking for, and with more detailed weather data, connect purchases to the weather a specific consumer experienced at a specific time and place. Secondly, our sample period is rather short, which limits our analysis of seasonal effects and changes in behavior over longer periods of time, such as some consumers getting used to biking in the rain. Access to more detailed data covering a period of multiple years would be ideal to use for future research on the topic.

Taken together, we find that while many consumers behave in line with the rational benchmark, a meaningful subset systematically overspends and suffers from weather-induced projection-bias in their contract choices. This thesis demonstrates that bounded rationality also plays a role in a routine and high frequency setting, and extends the current behavioral finance literature by challenging the neoclassical assumption of rational consumer behavior and highlighting the implications of bounded rationality in economic decisions in a new setting.

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