Projection Bias with Salient State-Dependent Utility

Lukas Buchheim Thomas Kolaska*

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Projection bias refers to the tendency to underestimate the effect of changes in the state of the world on future state-dependent utility. In this paper, we test whether projection bias affects advance sales for an outdoor movie theater. In this particularly simple setting, we expect projection bias to exert minimal influence on customers' decisions as their attention should be drawn to the state-dependence of utility for multiple reasons. First, we show that good weather is crucial for enjoying the movie. Second, the weather-risk associated with buying advance tickets is substantial and pointed out on the ticketing website. And third, customers can condition their purchase-decisions on unbiased weather forecasts. Nevertheless, we find that ticket sales are explained by purchase-date weather to a large degree. We rule out alternative explanations – such as information content of current weather, weather related shifts in the number of customers, and weather-related capacity constraints – implying that only projection bias can explain our findings.

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*Department of Economics, University of Munich, Geschwister-Scholl-Platz 1, 80539 Munich, Germany; Lukas Buchheim: lukas.buchheim@econ.lmu.de; Thomas Kolaska: thomas.kolaska@econ.lmu.de. We are indebted to Peter Mopils for providing us his sales data. For useful comments, we thank Jen Brown, Florian Englmaier, David Laibson, Devin Pope, Marta Serra-Garcia, Uwe Sunde, Joachim Winter, and seminar participants at the Universities of Munich and Warwick, the Workshop "Natural Experiments and Controlled Field Studies" in Holzhausen/Ammersee, the 6th "Nordic Conference" in Lund, the IMEBE 2012 in Castellón, the SMYE 2012 in Mannheim, the "Jahrestagung des Vereins für Socialpolitik 2012" in Göttingen, the "Annual Conference of the Royal Economic Society 2013" in London, and the IIOC 2013 in Boston. Financial support from the Deutsche Forschungsgemeinschaft through SFB/TR 15 (Lukas Buchheim) and GRK 801 (Thomas Kolaska) is gratefully acknowledged.

1. Introduction

In many economic decision problems, the utility from choice materializes in the future such that individuals need to predict their future utility in order to make informed decisions. While standard economic models assume that individuals predict their utility correctly, Loewenstein et al. (2003) argue that individuals make systematic errors; specifically, people tend to underestimate the extent to which changes in the state of the world alter utility. Hence, predicted future utility (at unknown future states) is biased towards utility at today's state. Loewenstein et al. call this error *projection bias*.

There is accumulating evidence that projection bias affects economic decisions like apparel and car purchases (Conlin et al., 2007; Busse et al., 2013) or college choice (Simonsohn, 2010). For example, in parallel work Busse et al. demonstrate that sales of 4-wheel drive vehicles increase by 6 percent after a snowstorm, that is at times when the weather-related utility from owning a 4-wheel drive is very high. All these papers have in common, however, that the weather-related dimension of utility, which serves as the testing ground for projection bias, is most likely not of primary importance for decision makers. Yet, if this is the case and individuals devote only limited attention to predicting the weather-related dimension of utility for available alternatives, they may be more prone to make errors in that dimension.[1] Therefore, it remains an open question whether people are able to overcome projection bias when their attention is drawn to the state-dependent nature of utility.

In this paper, we test for projection bias in a situation where state-dependent utility is at the center of decision maker's attention: We study online advance sales for an outdoor movie theater where customers are expected to focus on their weather-dependent utility for several reasons. First, utility of watching a movie outdoors is highly weather-dependent. One indicator for this is that ticket sales shortly before the screening – when no weather uncertainty is left – vary considerably with weather, but cannot be explained by other factors such as the movie's box office results. Second, tickets are a perishable good, as they are non-refundable and valid for one particular show only. The value of pre-purchased tickets hence diminishes considerably when the weather turns out to be bad as moviegoers are fully exposed to current weather conditions. Third, the weather risk is substantial as weather is highly variable at the movie's location. Fourth, customers are explicitly informed about the weather risk on the ticketing website and are hence aware of it when making their decisions.[2]

For these reasons, we expect to observe a "lower bound" of projection bias in our setting, not least because customers can condition their purchasing decision on reliable, unbiased, and free information provided by weather forecasts.

[1] See Schwartzstein (2012) for theoretical and Hanna et al. (2012) for empirical evidence on how limited attention impedes learning.

[2] On the website, this is stated as follows: "[When making a purchase] you must be aware of two things. First: We are going to screen the movie regardless of weather conditions. Second: You have to pay for your tickets even if you do not collect them at the box office." (authors' translation from https://www.didax.de/kms/index.php [22 November 2013]).

We find that the "lower bound" of projection bias is quite substantial as variations in purchase-date weather explain variations in advance sales to a large degree. Across different time horizons – the number of days tickets bought in advance ranging from one day up to three weeks – a one standard deviation increase in sunshine duration on a given day leads to an increase in sales on that day between 10 and 25 percent on average. Our findings are robust to considering different subsets of customers. Notably, the results do not change for customers who experienced rainfall during a previous show; the dependence of ticket orders on current weather is thus prevalent for customers who had the possibility to learn from previous bad surprises.

We rule out a number of alternative explanations for this finding. First, we show that purchase-date weather has at most negligible predictive power for movie-date weather, ruling out the possibility that current weather is an informative signal for future weather.

Second, we investigate whether the positive effect of purchase-date weather on aggregate sales merely reflects an increase in the number of potential customers who consider visiting the theater as an attractive leisure activity without affecting individual decisions directly. This may be the case, for example, if good current weather reminds people of the possibility to visit the theater. We use a strategy similar to Conlin et al. (2007) to distinguish between the latter explanation and projection bias by looking at the decision to collect the tickets that have been purchased in advance. If, on the one hand, projection bias affects individual purchase decisions, predicted utility of customers is upward biased at times of good purchase-date weather. Then, tickets are mistakenly purchased with a higher likelihood and should, as a consequence, expire more frequently. If, on the other hand, individual decisions are unbiased and purchase-date weather solely affects the aggregate number of potential customers, we expect no effect on tickets collected. We find a positive effect of purchase-date weather on the probability that tickets expire, providing further evidence for projection bias.

Third, we argue that weather-related market interactions cannot explain why sales depend on purchase-date weather. In particular, there may be a "precautionary" rationale for purchasing tickets at times of good weather as the latter may increase the perceived probability for the theater selling out in advance. However, this seems unlikely to be the sole explanation for our findings for two reasons. First, sales well in advance of the movie-date – when the probability for the theater selling out is essentially zero – are also weather-dependent. Second, we show that hourly variations in weather explain hourly changes in ticket sales. This is in line with projection bias but does not fit an explanation based on "precautionary" purchasing motives because the perceived probability of the theater selling out is unlikely to vary with hourly changes in weather.

By showing that projection bias affects individual decisions even in simple decision problems in which the state-dependence of utility is particularly salient, our paper complements the emerging literature on projection bias in economics discussed above.[3] In addition to this literature in eco-

[3] Another recent line of work structurally estimates the degree of projection bias as one among at least two deviations from rational behavior. Moreover, the decision problems studied in this literature – financial decision making (Kliger and Levy, 2008), cigarette consumption (Levy, 2010), or gym attendance (Acland and Levy, 2013) – are, again, rather complex.

nomics, there is a number of papers in psychology providing evidence for projection bias. This literature deals mostly with how current visceral states – for example hunger or sexual arousal – affect decision making; see Loewenstein and Schkade (1999) for an overview.[4] Because the arousal of visceral states is likely to hamper cognitive decision making, it is, however, unlikely that this literature finds a "lower bound" of projection bias.

Furthermore, it is important to note that projection bias is observationally equivalent to agents holding subjective beliefs that unconditionally assign the current state of the world a higher likelihood in the future (this has been pointed out by DellaVigna, 2009).[5] There is some evidence for agents holding these types of beliefs, which Fuster et al. (2010) call "extrapolation bias". For example, several papers in behavioral finance find that individuals tend to choose assets with high current returns more frequently even if current returns do not predict future ones (Benartzi, 2001; Kaustia and Knüpfer, 2008; Barber et al., 2009; Choi et al., 2009). Similar evidence comes from the literature on heterogeneous expectations (see Hommes, 2011, for an overview of the literature); for example, Chavas (2000) estimates that 47 percent of cattle producers use the current price as proxy for future prices when planning future supply, despite large fluctuations in price over time.

However, it is unlikely that we are identifying merely an effect of the current state on beliefs in our setting. In contrast to the problem of forecasting prices at unknown future dates that is analyzed in the literature just mentioned, the problem we are analyzing is well defined in the sense that customers need to predict the weather on a specific date (the movie-date) given high frequency (daily) information about the underlying stochastic process. Since, at the theater's location, the true predictive power of weather is essentially nil already two days in advance, it seems implausible that the perceived predictive power is independent of the forecast horizon. Nevertheless, we find the effect of weather on sales to be constant with respect to the forecast horizon. We hence show that the current state affects predictions of future (expected) utility even in a real-world situation, in which the choice problem is close to a textbook model of decision making under risk.

The remainder of the paper is structured as follows. In the next section we motivate why we regard weather as the key determinant of utility for visits to the outdoor movie theater. We further develop a simple model and derive predictions regarding how current weather may affect advance sales and the subsequent decision of customers whether or not to visit the theater. In Section 3 we describe our data. Section 4 discusses our main empirical findings. In Section 5 we evaluate the robustness of as well as alternative explanations for our findings. The last section concludes.

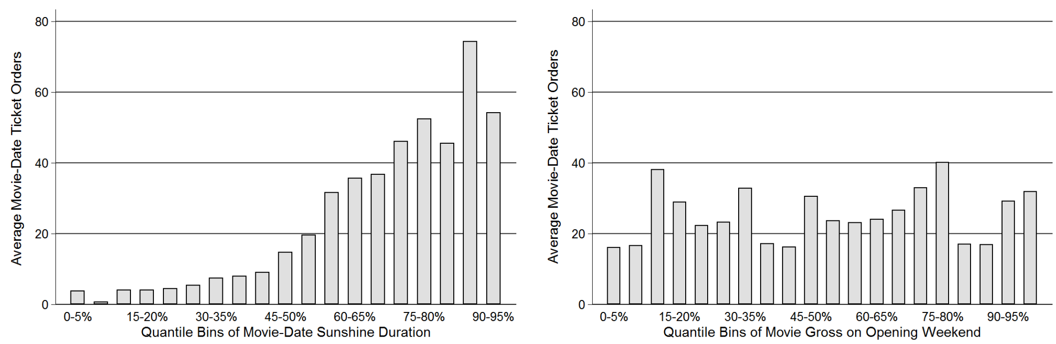
2. Weather and Utility: Model and Hypotheses

In this section, we first motivate why we regard weather as the key determinant of utility for customers of the cinema. We then formulate a simple model that nests two explanations for

[4]See for example Loewenstein (1996), Loewenstein et al. (1997), Read and van Leeuwen (1998), van Boven and Loewenstein (2003), and Nordgren et al. (2007).

[5]Recall that projection bias is a mistake in predicting utility at unknown future states. The beliefs regarding the likelihood of each state are assumed to be correct.

Figure 1: Relationship between Ticket Orders and Movie-Date Weather / Movie Popularity
This figure plots the average number of online ticket orders on the movie-date for bins based on five percent quantiles of movie-date sunshine duration (panel (a)) and of a movie's popularity measured by gross ticket sales on its opending weekend in Germany (panel (b)). Bins are sorted from dates with shortest sunshine duration / lowest movie gross to dates with longest sunshine duration / highest movie gross.



(a) Ticket Orders and Sunshine Duration (b) Ticket Orders and Movie Success

weather-dependent advance ticket sales and derive testable implications that guide our empirical analysis.

2.1. Weather and Utility

We test for projection bias in a decision problem in which decision maker's attention is plausibly drawn to the state-dependence of utility. This allows us to inquire whether projection bias is a robust feature of individual choice behavior or whether projection bias can be easily overcome by making decision makers aware of the state-dependence of their preferences.

The setting we are considering is unique, because we can assess the importance of weather for utility. We exploit that tickets are valid on one particular day only and that weather-related uncertainty is largely revealed on the movie-date. Hence, if good weather is crucial for customers to enjoy the movie night, variations in today's weather should result in substantial variations in ticket demand for today's screening. Moreover, we can assess the relative importance of weather for utility by comparing the effect of weather on demand with the effect of other potentially important characteristics – like the movie's general popularity in Germany.

Panel (a) of Figure 1 illustrates the effect of today's weather on online ticket orders for today's screening. We partition all movie-days between 2004 and 2011 in groups defined by five percent quantiles of average daily sunshine duration. For each of these groups, we plot the average number of movie-date online orders. Evidently, sunshine duration and the number of ticket orders are highly correlated. On days with sunshine duration below the 40 percent quantile, ticket orders for the same-day's screening are very low. Orders increase with sunshine duration substantially, though, once sunshine duration is above its median. These results also suggest that there is a large number of movie-dates, on which visiting the theater seems to be unattractive due to bad weather. Customers who buy tickets in advance hence take on a substantial weather risk.

In contrast, ticket orders and the movie's overall popularity are unrelated, as becomes evident from Panel (b) of Figure 1. For creating the figure, we plot the average number of movie-date ticket orders for each five percent quantile of the movie's gross ticket sales on the opening weekend in Germany.

Figure 1 hence suggests that good weather is crucial for customers to enjoy their visit of the outdoor theater, while the movie shown is of lesser importance. Noteworthy, this general result also emerges if we control for other factors that may affect movie-date ticket orders (like the day of the week) in regressions.

Finally, results from a survey that we conducted during the 2011 season indicate that customers themselves view weather as an important determinant of utility. Overall, 82 percent of respondents state that dry weather is either "very important" or "important" for having a good night at the movie.

2.2. Individual Purchase Decisions and Aggregate Sales

Individual Decisions Motivated by the evidence that customer's utility crucially depends on highly variable weather, we assume for modeling purposes that customers focus exclusively on their weather-related utility when considering to buy a ticket in advance.[6] More specifically, we assume that a customer's utility is given by $u(w_\tau)$, where $w_\tau \in \mathbb{R}$ represent weather conditions on date τ. The utility function $u(\cdot)$ is assumed to be increasing, twice differentiable, and concave on the real line. When not visiting the theater, individuals receive utility $u(\eta)$ from a heterogeneous outside option $\eta \in \mathbb{R}$, which is distributed within the population according to the distribution $G(\cdot)$.[7]

On the purchase-date $t < \tau$, an individual decides whether or not to buy a ticket for the movie-date at costs c (in utility terms). On the purchase-date, the realization of weather on the movie-date is uncertain. We denote the distribution of w_τ at t by $H(\cdot)$, which is known to potential customers. We assume that $H(\cdot)$ belongs to the location family of distributions with location parameter f_t and is independent of actual weather w_t (we will justify this assumption empirically in Section 5.1).[8] The parameter f_t denotes the weather forecast at t for the movie-date τ, which is available to individuals free of charge. The forecast predicts expected weather on the movie-date and contains all relevant information regarding movie-date weather at t: $E[w_\tau | f_t] = E[w_\tau | f_t, w_t] = f_t$, where E

[6] For example, we abstract from determinants of utility such as the popularity of the movie. In the setting we are analyzing, these determinants are orthogonal to weather such that omitting them in this analysis does not alter the empirical implications of the model. We control for popularity of the movie via its box-office results in one of the robustness checks discussed in Section 5.3.

[7] Assuming a weather-independent outside option simplifies the problem and is a way of capturing individual heterogeneity – like preferences for a particular movie – in the model. For our result, however, it would be sufficient if the impact of weather on $u(w_\tau)$ is stronger than on the outside option. This is satisfied if going to the movie is the utility maximizing option for particularly good realizations of weather, which is likely to be the case given the evidence above.

[8] In practice, $H(\cdot)$ may depend on the forecast horizon $\tau - t$ and the season of the year as well. Considering these factors does not change the analysis; we omit them for notational convenience.

is the expectations operator with respect to $H(\cdot)$. We will show in Section 5.1 that this assumption is consistent with reality.

To incorporate projection bias in our model, we adopt the formulation of "simple projection bias" (Loewenstein et al., 2003) and assume that the current state – current weather – receives weight $\alpha \in [0,1]$ in an agent's expected utility function. Clearly, the case $\alpha = 0$ represents fully rational behavior. The case $\alpha > 0$ captures that individuals cannot fully assess the extent to which a change in the state of the world will alter their utility and thus unconsciously anchor their utility on the current state.

Expected utility from purchasing a ticket on the purchase-date for an individual with outside option η is then given by

$$v^B(f_t, w_t, \eta) = (1 - H(\eta)) \Big((1-\alpha) \, E[u(w_\tau) | \, w_\tau \geq \eta, f_t] + \alpha u(w_t) \Big) + H(\eta) \, u(\eta) - c. \tag{1}$$

A customer who owns a ticket will only visit the theater if movie-date weather exceeds the outside option ($w_\tau \geq \eta$). In this case, captured by the first term of (1), she receives weather-related (expected) utility from visiting the theater, which may have excessive weight on the current state. If movie-date weather turns out to be unexpectedly bad ($w_\tau < \eta$), she will let her ticket expire and choose the outside option instead. In either case, she has to bear the ticket costs c.

Clearly, an individual with outside option $\bar{\eta}$ will be indifferent between buying and not buying a ticket on the purchase-date iff

$$F^P(f_t, w_t, \bar{\eta}) \equiv v^B(f_t, w_t, \bar{\eta}) - u(\bar{\eta}) = 0 \tag{2}$$

A natural candidate for optimal choice behavior is that all individuals with low outside options $\eta \leq \bar{\eta}$ buy tickets on the purchase-date and all individuals with high outside options $\eta > \bar{\eta}$ do not. Lemma 1 below states that optimal choices can indeed be completely described by a unique $\bar{\eta}$ satisfying (2). Before stating the lemma, however, we need to assume sufficient conditions for the existence of a unique fixed point of (2).

Assumption 1.

(i) For all f_t there exists an η satisfying $F^R(f_t, \eta) \equiv (1 - H(\eta)) \left(E[u(w_\tau) | \, w_\tau \geq \eta, f_t] - u(\eta) \right) - c = 0$.

(ii) The hazard rate of $H(\cdot)$, $h(w)/(1 - H(w))$, is weakly increasing.

Assumption 1 (i) ensures that there is at least one potential customer who, given the optimal use of information, would be indifferent between buying a ticket on the purchase-date and not buying a ticket at all. This ensures existence of a fixed point of (2). Assumption 1 (ii) is the monotone hazard rate assumption, which provides a sufficient condition for uniqueness of the fixed point and holds for a variety of frequently used distributions like the normal and uniform distributions. Throughout the paper we will maintain Assumption 1, which allows us to state the following result:

Lemma 1. *Under Assumption 1, a unique $\bar{\eta}$ satisfying (2) exists for all (f_t, w_t).*

All proofs are relegated to the appendix. A direct implication of the above lemma is that there is always a positive probability, $G(\bar{\eta}) \in (0,1)$, that some customer will buy a ticket on the purchase-date.

Aggregate Sales Given the individual propensity to buy a ticket, expected aggregate sales depend on the total number of potential customers. Here, we incorporate the idea in our model that good weather makes the choice option "outdoor movie theater" more salient and thus enlarges the customer base. One possible interpretation is that customers face cognitive restrictions regarding the number of choice options they can consider at a given time. For this reason, they consider a choice option only if it "comes to mind", which is supposed to be positively related to its attractiveness at the current state.[9]

If the number of potential customers is weather-dependent, ticket sales may be driven by weather even if individual decisions to buy tickets are fully rational. To allow for this explanation in our model, we assume that the number of potential customers $n(w_t)$ is increasing in purchase-date weather w_t. The expected total number of sales on purchase-date t is thus given by $y(f_t, w_t) = n(w_t)\,G(\bar{\eta}(f_t, w_t))$. If customers are fully rational, i.e. they have all choice options in mind at all times, $n(\cdot)$ is independent of w_t.[10]

2.3. Hypotheses

Our empirical analysis in Section 4 is guided by testable predictions derived from the model. Our first hypothesis deals with the effect of purchase-date weather on sales.

Hypothesis 1. *If customers are rational ($\alpha = 0$ and $\partial n(w_t)/\partial w_t = 0$) advance sales are independent of purchase-date weather. Otherwise, sales increase when purchase-date weather is good.*

Hypothesis 1 states that, if variations in purchase-date weather explain variations in advance sales, customers' decisions are either affected by projection bias or good weather reminds customers of the possibility to visit the movie theater.

If purchase-date weather and ticket sales are correlated, we moreover conjecture that customers are unaware of the behavioral limitations underlying the weather-dependence of their choices. Otherwise, they could adopt strategies to arrive at optimal decisions nevertheless such as conditioning decisions on the weather forecast. If customers' decisions are unconsciously affected by weather, however, we expect the effect of weather on sales to be of similar magnitude independently of the particular characteristics of the choice problem like the time between purchase-date and movie-date (to which we will refer as "sales horizon"), or the customer's past experiences with visiting the theater.

[9] Another possible interpretation for a weather-dependent customer base is that good weather at the purchase-date facilitates the coordination of larger groups.

[10] A third possible explanation for a positive relation between good weather on the purchase-date and sales is that customers expect the theater to be sold out with higher probability. We discuss this potential explanation theoretically after Hypothesis 2 and empirically in Section 5.2.

Furthermore, we derive testable predictions to disentangle whether purchase-date weather affects individual decisions via projection bias or merely the total number of potential customers. This requires to examine individual choices which we only observe for the decision whether or not to collect pre-purchased tickets on the movie-date.

Our model predicts that individuals buy a ticket if their outside option η is worse than the cutoff $\bar{\eta}$ and let it expire if movie-date weather is sufficiently bad ($w_\tau < \eta$). The probability that a customer lets her ticket expire is therefore given by

$$\Pr(\text{expire} \mid \text{ buy}) = \Pr(w_\tau < \eta < \bar{\eta}) = \begin{cases} 1 - G(w_\tau)/G(\bar{\eta}) & \text{if } w_\tau < \bar{\eta} \\ 0 & \text{else.} \end{cases} \tag{3}$$

If individual purchase decisions are affected by current weather, good weather increases the predicted utility of buying tickets in advance and thus leads to a higher $\bar{\eta}$. Since the realization of movie-date weather w_τ is independent of purchase-date weather w_t, the likelihood that a customer prefers her outside option on the movie-date hence increases if purchase-date weather was nice. In contrast, if current weather has no effect on individual decisions, the likelihood of ticket collection is independent of purchase-date weather. The following hypothesis summarizes this argument.

Hypothesis 2. *If customers are rational ($\alpha = 0$ and $\partial n(w_t)/\partial w_t = 0$) or if current weather increases the number of potential customers ($\partial n(w_t)/\partial w_t > 0$), the probability that tickets expire is independent of purchase-date weather. Otherwise – if individual decisions are affected by projection bias ($\alpha > 0$) – the probability that tickets expire increases with purchase-date weather w_t if and only if for movie-date weather it holds that $w_\tau < \bar{\eta}$.*

Before we continue, it is important to point out a few assumptions upon which our model and thus our hypotheses rests. First, as noted above, we assume that purchase-date weather contains no information for movie-date weather. Otherwise, our results could be explained by customers taking current weather as informative signal. We show in Section 5.1 that purchase-date weather is indeed not informative. Nevertheless, individuals could perceive current weather to be informative for the future. If the perceived information content of projection bias is independent of the "sales horizon", this is observationally equivalent to projection bias. However, it is natural to assume that the perceived information content of current weather is declining with the time horizon one is trying to predict. Then, the effect of purchase-date weather on sales should become weaker with increasingly long horizons. In Section 5.2 we will see that this is not the case.

Finally, to keep the model simple we have abstracted from the fact that potential customers essentially face a dynamic problem when they decide on which date they would like to buy their tickets. Clearly, the timing of buying tickets can be affected by purchase-date weather, for example if the latter affects the perceived probability that the theater may sell out. We discuss this potential alternative explanation in more detail in Section 5.2.

3. Data

In this section, we describe the data that we use for the empirical analyses in Sections 4 and 5. Furthermore, we augment the description of the data by highlighting the typical weather patterns at the theater's location (Munich, Germany). We will see that the weather in Munich changes frequently during the summer months. This is important, because we argued that potential customers of the theater are expected to forecast their weather-related utility carefully, due to both, the generally instable weather conditions and the aforementioned importance of good weather for the overall enjoyment of the movie night.

3.1. Weather and Forecast

Due to the proximity of the Alps, the weather in Munich is highly variable during the season of the outdoor theater, which typically covers the months of June to August. This manifests itself in high monthly precipitation in the summer months, when total precipitation is on average 123 mm per month (for comparison: London 51 mm, New York City 92 mm, and Berlin 61 mm).[11] In addition, long periods of stable good weather are the exception. Rather, there are frequent shifts in weather conditions: on average, there are 12.4 rain days (days with at least 1 mm of rain) per month between June and August (for comparison: London 10.5 days, New York City 8 days, and Berlin 8.7 days).

For our empirical analyses, we use high quality weather data from the weather station of the Meteorological Institute of the University of Munich. The data comprises of hourly measures of sunshine duration (as fraction of time), rainfall (measured in mm per hour), and temperature (in degree Celsius). For most analyses, we use daily averages of these weather variables, where we restrict attention to sunshine duration between 8 am and 7 pm in order to not confound our measures by the changing times of dusk and dawn.

Further evidence concerning the instability of local weather in Munich is contained in the summary statistics of the weather variables in Table 1. The between-day variation in weather can be read from the first two columns; the first (second) column reports the average sunshine duration between 8 am and 7 pm (between 5 pm and 7 pm) as well as 24 hour averages (averages between 7 pm and 11 pm) of hourly rainfall and temperature. Compared to their respective means, standard deviations of sunshine duration and rainfall are high; for the daily averages, the coefficients of variations are 1.55 for sunshine duration and 0.45 for rainfall. In addition, note that in the evening average precipitation per hour is almost twice as high as during the entire day.

To gauge the extent of within-day variation in weather, we report the mean of the within-day (i.e. across hours) standard deviations of all weather variables. Again, sunshine duration and precipitation exhibit high within-day variation. The within-day variation of temperature should, however, be interpreted with caution, for there is a cyclical pattern of temperature on each day.

[11] Sources of long term monthly averages: World Meteorological Organization http://worldweather.wmo.int/ [4 October 2012].

Table 1: Summary Statistics: Weather and Forecast

	Weather		
	All day	Evening	SD within day
Avg. Sunshine Duration	0.53	0.47	0.20
	(0.34)	(0.38)	(0.14)
Avg. Rainfall per Hour	0.11	0.19	0.28
	(0.24)	(0.63)	(0.63)
Avg. Temperature	18.98	19.14	3.02
	(3.89)	(4.24)	(1.28)
	Forecast		
	Minimum	Maximum	
Forecasted Temperature	12.66	23.56	
	(2.75)	(4.02)	

Notes: We report means and standard deviations (in parentheses). Sunshine duration is mesured as fraction of time, temperature is measured in degrees Celsius, and rainfall is measured in mm per hour. In the column "SD within day" we report the average of the variable's standard deviations across hours within a single day.

To control for the weather forecast, we hand-collect the forecast from the archives of the daily newspaper “Süddeutsche Zeitung”, which is published every day except Sundays and public holidays.[12] It provides a regional forecast for each day, one to four days into the future, for the greater Munich area. The forecast comprises forecasted maximum and minimum temperature (in degrees Celsius) and one of the following weather symbols: sunny, partly sunny, scattered thunderstorms, shower, and rain.[13]

The summary statistics of minimum and maximum forecasted temperature are displayed in Table 1. As expected, they are in a similar range as average temperatures. The distribution of forecast symbols – which does not vary substantially by forecast horizon – is again indicative of the variable weather in Munich during the summer: Rather unstable weather conditions like scattered thunderstorms (11 percent of days) and shower (42 percent of days) are forecasted for more than half of the days in our sample. Sunny or partly sunny conditions are forecasted for 44 percent of days and rain is forecasted for 3 percent of days.

3.2. Ticket Sales

The data on ticket sales were provided by “Kino, Mond und Sterne” [Movies, Moon, and Stars], one of four outdoor movie theaters in Munich. The theater has a total of 1,300 seats available, tickets for which are sold at the box office and various advance ticket sales locations.[14] Because the movie is shown regardless of weather conditions, tickets are non-refundable. Customers who buy

[12]Historic weather forecasts are not stored by any German weather firm due to their memory-intensity.
[13]There are in total 12 observations of the symbol overcast, which we group with “shower” to simplify the exposition of results. Undoing this grouping does not lead to any significant changes throughout.
[14]Ticket prices have been stable at 5.70 Euro (about 7.85 Dollar) each during the entire period.

Table 2: Summary Statistics: Ticket Orders

	Day of Show	1 Day Out	2 Days Out	3 Days Out	4 Days Out
Avg. Daily Ticket Orders	24.74	7.18	2.78	1.36	0.89
	(33.97)	(10.82)	(4.30)	(2.24)	(1.37)
Tickets per Order	2.46	2.55	2.55	2.63	2.58
	(0.69)	(0.92)	(0.88)	(1.24)	(1.24)

Notes: We report means and standard deviations (in parentheses) of daily ticket orders and of the number of tickets per order for all orders on the movie-date as well as one to four days out.

their ticket in advance hence bear the full weather risk.[15] For each order, the system records the number of tickets purchased, the exact date of the transaction, the birth date of the customer, as well as a unique alphanumeric customer ID which allows us to track repeat customers.

Online sales constitute a substantial fraction of total ticket sales. Between the years 2009 and 2011, for which we know the overall number of sales, online sales amount to 24 percent of total ticket sales. Thereby, more than half (almost 60 percent) of online tickets are sold on the day of the show, when there is merely little uncertainty left. For this reason our main analysis focuses on sales between one and four days in advance, for which there is data on the weather forecast available. In this time, 30 percent of online tickets are sold, with percentages declining the earlier tickets are purchased. The remaining 10 percent of online tickets are sold five and more days before the show.

Our main variable of interest is aggregate ticket orders on a daily base. More precisely, one observation is the sum of ticket orders on a single day for a specific show. If no tickets are sold on a day at most 23 days before the show, we add an observation with aggregate orders of zero. This results in at least 24 observations for every single movie shown, one for each day between 0 and 23 days out.

The summary statistics for ticket orders are presented in Table 2, organized according to how early in advance tickets were sold. The average number of ticket orders decreases from 7 one day out to 1 four days out, representing the declining pattern of orders. The number of tickets sold per order remains stable at about 2.6, independent of the time horizon. About half of the ticket orders are placed by repeat customers, who have bought tickets online more than once.

For the years 2009 – 2011, we additionally know for each order whether tickets were, in fact, collected at the evening of the show. Of the total of 4,102 online orders in those years, the vast majority (88 percent) of tickets was collected.

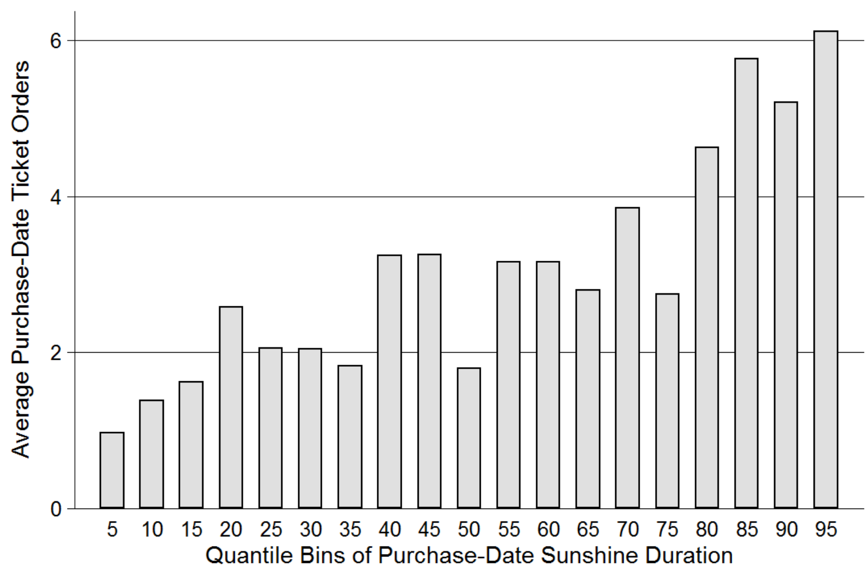
3.3. Survey

During the 2011 season, we conducted a survey among visitors of the cinema. Overall we received 443 questionnaires at 13 different days with considerable variance in weather conditions (and accordingly varying number of questionnaires obtained per day). This amounts to more than 10 percent of the audience on these days on average. The purchasing behavior of the surveyed cus-

[15] None of the seats are covered. See Appendix C for a picture of the theater.

Figure 2: Relationship between Ticket Orders and Purchase-Date Weather

This figure plots the average number of daily ticket orders between one and four days in advance for bins based on five percent quantiles of purchase-date sunshine duration. Bins are sorted from dates with shortest sunshine duration to dates with longest sunshine duration.



tomers matches overall purchasing behavior very well: 25 percent of surveyed customers bought their ticket online (compared to 24 percent of all customers between 2009 – 2011) and 7 percent purchased it between one and four days in advance (compared to 8 percent of all customers). Throughout, we use the survey to provide supporting evidence for our arguments. That being said, none of our results depends on data from the survey.

4. Empirical Analysis

In this section we test the hypotheses derived in Section 2. We first show that weather on the purchase-date explains variation in ticket orders for various model specifications, rejecting rational behavior from Hypothesis 1. Furthermore, we show that good weather on the purchase-date increases the likelihood that the purchased tickets expire, providing evidence for projection bias (Hypothesis 2).

4.1. Purchase-Date Weather and Ticket Orders

Figure 2 illustrates the effect of weather on ticket orders by comparing the number of orders across different weather conditions on the purchase-date. For the sample of ticket orders one to four days ahead of the movie date – which we use in the empirical analysis below – we group ticket orders into bins based on five percent quantiles of purchase-date sunshine duration and plot, for each of these bins, the average number of ticket orders per day. Consistent with projection bias, Figure 2 shows that the average number of daily ticket orders rises parallel to an increase in sunshine duration from the left to the right of the horizontal axis. Hence, advance ticket orders are correlated with purchase-date weather, even though current weather is irrelevant for enjoying the movie on a later date.

An obvious concern with the graphical analysis above is that other factors which explain ticket sales – like the weather forecast – may possibly be correlated with purchase-date weather. To address this concern, we estimate the effect of purchase-date weather on daily ticket orders in a number of regressions.

The dependent variable in all these regressions is normalized ticket orders, $y_{\tau t}/\bar{y}_{\Delta}$, where $y_{\tau t}$ is the number of ticket orders on the purchase-date t for the movie-date τ, and $\bar{y}_{\Delta}$ is the sample mean of ticket orders $\Delta = \tau - t$ days in advance. Estimated coefficients of our empirical models are hence predicted changes in ticket orders as a fraction of mean orders for a given horizon. This allows us to compare the magnitude of the estimated coefficients for the independent variables across different sales horizons Δ. Without the normalization, the magnitude of estimated coefficients would reflect the variation in the (mean) number of ticket orders $y_{\tau t}$ that is due to how far in advance ticket orders are placed.

As indicators of purchase-date weather, we include average sunshine duration as well as average hourly precipitation at t as explanatory variables (collected in the weather vector $\mathbf{W_t}$) in all regressions.[16] In addition, we control for the weather forecast at t for the movie-date τ by adding the forecasted maximum and minimum temperatures, as well as separate dummy variables for each forecast symbol as independent variables; these variables are collected in the forecast vector $\mathbf{F}_{\tau\mathbf{t}}$. Because the forecast is only available for a horizon Δ of up to four days, we limit the sample to ticket orders between one and four days ahead of the show for now. We will investigate the determinants of ticket orders five days or earlier before the movie-date in Section 5.2.

For the first empirical model we organize the data in a panel structure with day of the show τ as unit of observation and advance sales one to four days out being observations over time. Within this structure the model is

$$y_{\tau t}/\bar{y}_{\Delta} = \mathbf{W}'_{\mathbf{t}}\beta_{\mathbf{W}} + \mathbf{F}'_{\tau\mathbf{t}}\beta_{\mathbf{F}} + \mathbf{D}'_{\tau\mathbf{t}}\beta_{\mathbf{D}} + v_{\tau t}, \tag{4}$$

where $\mathbf{D}_{\tau\mathbf{t}}$ includes dummy variables for each time horizon Δ between purchases and show. We assume that the error term $v_{\tau t}$ is iid between different shows τ but may be arbitrarily correlated between advance sales for the same show. To control for unobserved heterogeneity across movie-dates that may possibly be correlated with our regressors, we estimate (4) as a fixed effects model.

For the second econometric model we organize our data as cross sections separately for each purchase-date being $\Delta \in \{1,2,3,4\}$ days ahead of the movie-date. This gives us less power due to limiting observations, but allows us to exploit cross sectional variation and to include a set of

[16] We omit average temperature from our analysis, since it is highly correlated with sunshine duration. We chose to keep sunshine duration due to its greater salience. However, our results are qualitatively not affected by this choice. For further details see the discussion in Section 5.3.

controls $\mathbf{X}_{\tau\mathbf{t}}$, which are for most observations time invariant between t and τ. Specifically, we control for the weekday of the show, average sunshine duration and precipitation of the past two weeks before t, as well as dummy variables for year and month. For each Δ, we estimate the following model:

$$y_{\tau t}/\bar{y}_{\Delta} = \mathbf{W}'_{\mathbf{t}}\beta_{\mathbf{W}} + \mathbf{F}'_{\tau\mathbf{t}}\beta_{\mathbf{F}} + \mathbf{X}'_{\tau\mathbf{t}}\beta_{\mathbf{X}} + \varepsilon_{\tau t}. \tag{5}$$

Since $\Delta = (\tau - t)$ is fixed, there is a single observation for each movie night τ. Imposing the identifying assumption from above – that errors $\varepsilon_{\tau t}$ are uncorrelated across movie-dates τ – we can estimate (5) by OLS. Before we proceed, it should be noted that as an alternative empirical strategy we could use count data models equivalent to (4) and (5) to estimate coefficients with similar interpretations. This strategy yields virtually unchanged results throughout the paper.

Table 3 displays the estimation results for the two models. Similar to the graphical analysis in Figure 2, the results provide strong support for Hypothesis 1. Despite being irrelevant for enjoying the movie night, purchase-date weather – in particular sunshine duration – affects ticket orders in an economically and statistically significant way. A one standard deviation increase in sunshine leads, on average, to an increase in ticket orders of more than 17 percent of mean orders. Noteworthy, the magnitude remains strikingly similar across specifications. This would be expected if projection bias was driving the result, because decisions should be biased in a similar manner independent of the purchase horizon.[17]

Another way to interpret the magnitude of purchase-date weather is to compare it to the effect of the weather forecast on orders. In the cross-sections for ticket orders one to three days before the movie-date, a one standard deviation increase in the predicted maximum temperature leads to an increase in ticket orders of about 40 percent.[18] The effect of purchase-date weather on ticket orders is thus about half as big as that of forecasted temperature. However, consistent with rational behavior, the effect of the weather forecast on ticket orders declines for earlier purchase-dates along with the deteriorating quality of the forecast; this can be seen by the decrease in predictive power of the forecast variables overall. In contrast and consistent with a behavioral bias affecting purchasing behavior, the effect of purchase-date weather remains stable throughout. We hence summarize our findings thus far as follows:

Result 1. *Purchase-date weather has a statistically and economically significant effect on aggregate ticket orders.*

We further investigate our earlier conjecture (from Section 2.3) that the effect of weather on ticket orders is independent of customers' past experiences. This is to address the concern that the results are driven by inexperienced customers. To this end, we estimate the effect of weather

[17] The regression coefficients of average rainfall per hour provide further, albeit less clear-cut, evidence for purchase-date weather affecting ticket orders. Here, projection bias should lead to a negative coefficient; this is the case for three out of five specification. While these estimates are economically significant in magnitude, they are only borderline statistically significant at best.

[18] In the fixed effects estimates in the first column, neither of the forecast variables has a statistically significant impact on ticket orders. We conjecture that this is due to limited "within-variance" of the forecast for one particular day which is the identifying variation in this specification.

Table 3: Effect of Purchase-Date Weather on Ticket Orders

	Normalized Ticket Orders				
	Fixed Effects	1 day out	2 days out	3 days out	4 days out
Avg. Sunshine Duration	0.49***	0.47**	0.68***	0.45*	0.57**
	(0.11)	(0.21)	(0.21)	(0.25)	(0.24)
Avg. Rainfall per Hour	−0.20	−0.36*	0.48	−0.45*	0.21
	(0.17)	(0.20)	(0.46)	(0.27)	(0.40)
Forecasted Maxtemp.	0.019	0.092***	0.093***	0.10***	0.054
	(0.017)	(0.025)	(0.032)	(0.031)	(0.033)
Forecasted Mintemp.	−0.021	0.084**	0.039	−0.0100	0.029
	(0.023)	(0.034)	(0.043)	(0.042)	(0.036)
Symbol Partly Sunny	0.099	−0.54*	−0.87**	0.12	−0.62**
	(0.13)	(0.31)	(0.35)	(0.30)	(0.27)
Symbol T-Storm	0.0091	−1.49***	−0.70*	0.24	−0.15
	(0.17)	(0.33)	(0.38)	(0.35)	(0.40)
Symbol Shower	−0.066	−0.95***	−1.22***	−0.18	−0.55**
	(0.14)	(0.32)	(0.33)	(0.29)	(0.26)
Symbol Rain	−0.096	−1.27***	−1.18***	0.26	−0.25
	(0.20)	(0.37)	(0.42)	(0.44)	(0.61)
2 Days Out	0.026				
	(0.059)				
3 Days Out	0.016				
	(0.078)				
4 Days Out	0.087				
	(0.084)				
Constant	0.61	−2.84***	−0.69	−1.50**	0.091
	(0.46)	(0.68)	(0.61)	(0.73)	(0.68)
Time-invariant Controls	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1554	393	390	384	383
Overall (FE model)/Adjusted R^2	0.100	0.344	0.314	0.207	0.194

Notes: We report the coefficients and robust standard errors from regressions of normalized daily ticket orders between one and four days in advance on purchase-date weather conditions (average sunshine duration as fraction of time, average hourly rainfall in mm), the forecast for the movie-date (maximum and minimum temperature in degree Celsius, mutually exclusive forecast indicators), and control variables (dummies for the sales horizon, weekday of the movie-date, year, and month, as well as two week moving averages of past sunshine duration and rainfall). The omitted forecast indicator is "sunny". In the first column, we estimate the panel model (4) including fixed effects for the movie-date; standard errors are clustered on the movie-date level. In the remaining columns, we estimate model (5) for the cross-sections of ticket orders for each sales horizon separately. Across specifications, daily ticket orders for a particular movie-date are normalized by the mean of ticket orders conditional on the sales horizon. Coefficients are hence to be interpreted as increases in orders as a fraction of horizon-specific mean orders. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

on normalized ticket orders via the fixed effects model (4) for three different subsets of repeat customers. These are, first, customers who place at least the second order within the entire period between 2004 and 2011, second, customers who place at least the second order within any given season, and third, customers who place an order after having experienced rainfall during a show they previously purchased tickets for. For each subset of customers, we calculate normalized ticket orders as before. That is, we aggregate all ticket orders on a given purchase-date for a given movie-date by customers within a particular subset; aggregate orders are then normalized by mean orders of the respective set of customers for the horizon Δ between purchase- and movie-date.

Table 8 in Appendix B shows that ticket orders of all subsets repeat customers are equally affected by weather as orders of all customers. This holds especially for customers with the unfortunate experience of rainfall during a previous visit. Ticket orders to this class of customers is predicted to increase, on average, by 26 percent given a one standard deviation increase in sunshine duration.[19]

4.2. Purchase-Date Weather and Ticket Collection

We now analyze customer's decision whether or not to collect their advance tickets. This allows us to assess whether current weather affects ticket orders by increasing the number of potential customers (reminder effect of weather) or by changing individual behavior (projection bias).

Hypothesis 2 predicts that an increase in current day's sunshine duration increases the likelihood that customers let their tickets expire if decisions are affected by projection bias (and movie-date weather is an unpleasant surprise). In contrast, if good weather today merely increases the number of potential customers, the decision to actually visit the theater should be independent of purchase-date weather.

Let the decision of a customer i, who has purchased a ticket on date t for a movie at τ, to collect her ticket be denoted by $\psi_{it\tau} = 0$ and the decision to let the ticket expire by $\psi_{it\tau} = 1$. The likelihood that a customer does not use her ticket on the movie-date is estimated using the Probit model

$$Pr(\psi_{it\tau} = 1) = \mathbf{\Phi}(\mathbf{W}_\mathbf{t}'\beta_{\mathbf{Wt}} + \mathbf{W}_\tau'\beta_{\mathbf{W}\tau} + \mathbf{F}_{\tau\mathbf{t}}'\beta_\mathbf{F} + \mathbf{D}_{\tau\mathbf{t}}'\beta_\mathbf{D}). \tag{6}$$

Since the model predicts that individual collection decisions depend on movie-date weather, we include movie-date weather $\mathbf{W}_\tau$ on the right hand side of (6) additional to purchase-date weather $\mathbf{W_t}$, forecast $\mathbf{F}_{\tau\mathbf{t}}$, and horizon dummies $\mathbf{D}_{\tau\mathbf{t}}$ as defined in Section 4.1.

The first column of Table 4 reports the estimated coefficients from model (6) for all customers who had purchased tickets one to four days in advance in the years 2009 to 2011. Extended sunshine duration on the purchase-date tends to increase the likelihood that tickets sold in advance are not collected. However, the estimated coefficients are significantly different from zero only at the 12 percent level. We conjecture that this is due to limited variance of the dependent variable: less than 7 percent of customers let their tickets expire. In fact, the model predicts that the probability for advance tickets to expire unconditionally equals zero if the realized weather at the movie turns

[19] Although we only report the results from the fixed effect model (4), similar results are obtained from model (5).

Table 4: Effect of Purchase-Date Weather on Ticket Collection

	1 if Tickets Expire, 0 if Tickets Used		
	Full Sample	Movie Sunshine less than at Purchase	Movie Sunshine less than Predicted
Avg. Purchase-Date Sunshine Duration	0.26	0.63*	0.56**
	(0.16)	(0.35)	(0.25)
Average Predicted Likelihood that Tickets Expire			
At Sunshine Duration = 0	0.05	0.06	0.09
At Sunshine Duration = 1	0.08	0.14	0.18
Avg. Purchase-Date Rainfall per Hour	−0.01	0.09	−0.11
	(0.23)	(0.36)	(0.33)
Sunshine before the Movie	−0.66***	−0.76***	−1.57***
	(0.15)	(0.24)	(0.47)
Rainfall per Hour during the Movie	0.09*	0.09	0.11*
	(0.05)	(0.06)	(0.06)
Temperature during the Movie	−0.15***	−0.15***	−0.17***
	(0.02)	(0.03)	(0.03)
Forecast	*Yes*	*Yes*	*Yes*
Horizon Dummies	*Yes*	*Yes*	*Yes*
Observations	2628	1003	868
Pseudo R^2	0.21	0.20	0.21

Notes: We report the coefficients and robust standard errors of Probit regressions of the customer's decision to let her tickets expire on purchase-date weather conditions (average sunshine duration as fraction of time, average hourly rainfall in mm), movie-date weather conditions (average sunshine duration between 5 pm and 7 pm, average hourly rainfall and average temperature in degree Celsius between 7 pm and 11 pm), the forecast from the purchase- for the movie-date (maximum and minimum temperature, mutually exclusive forecast indicators), and dummies for the sales horizon. In the first column, we do so for the full sample of advance sales (with purchase-date between one and four days before the movie-date) in the years 2009 to 2011. In the second column, we restrict the sample to orders for which average sunshine duration was lower on the movie- than on the purchase-date. In the third column, we restrict the sample to orders at which average movie-date sunshine duration between 5 pm and 7 pm was lower than predicted on the purchase-date using model (7). We further report, for each sample, the average predicted likelihood that tickets expire if average purchase-date sunshine duration is one (completely sunny) and zero (completely cloudy). Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

out to be at least as good as the outside option of the marginal customer (i.e. if $w_\tau \geq \bar{\eta}$). In other words, our model predicts that customers should decide to let their tickets expire only in cases in which movie-date weather is a negative surprise. Hence, we conjecture that the effect of purchase-date weather on the likelihood of ticket collection is diluted due to the relatively large number of customers who are predicted to collect their ticket with certainty.

To test this conjecture, we re-estimate (6) for two sub-samples of customers, for which movie-date weather can be considered to be an unpleasant surprise. For the first sub-sample, we only consider customers, who experienced higher average sunshine duration on the purchase- than on the movie-date. For the second sub-sample, we only consider customers for whom expected sunshine duration $\hat{S}_t$ as predicted by the forecast via model (7) in Section 5.1 is lower than realized sunshine duration shortly before the movie starts. The two sub-samples are chosen in a way that our model predicts a positive probability for tickets to expire (i.e. $w_\tau < \bar{\eta}$) for risk-averse customers whose degree of projection bias α takes the extreme values $\alpha = 1$ (for the first sub-sample) and $\alpha = 0$ (for the second sub-sample).[20]

Given the arguments from the model, the probabilities that their advance tickets expire should be considerably higher for customers within the two sub-samples than for the customers dropped from the samples. Indeed, less than 4 percent of customers dropped from either of the two sub-samples do not collect their tickets, while between 12 percent and 14 percent of tickets expire within the two sub-samples.

The results from re-estimating (6) for the two sub-samples are depicted in columns (2) and (3) of Table 4. In both sub-samples, we find a significant positive relationship between the likelihood that tickets expire and purchase-date sunshine duration. The estimated coefficients thereby imply that customers in the respective samples are, on average, more than twice as likely to let their ticket expire when purchased on a sunny day ("Avg. Sunshine Duration" equals one) compared to a completely cloudy day ("Avg. Sunshine Duration" equals zero). For the first sub-sample (movie-date weather worse than purchase-date weather) in column (2) the corresponding likelihood increases from 5.7 to 13.9 percent, and for the second sub-sample (movie-date weather worse than expected) in column (3) the predicted likelihood increases from 8.6 to 17.7 percent.[21] This leads to our second result.

Result 2. *Customers are more likely to let their tickets expire on the movie-date if they experienced good weather on the purchase-date, providing evidence for projection bias (Hypothesis 2).*

[20] To see this, note that for the case of risk-neutrality (2) implies $\bar{\eta} > \alpha w_t + (1-\alpha)E[w_\tau | w_\tau \geq \bar{\eta}, f_t]$. Hence, for $\alpha = 1$ and $w_\tau < w_t$, we have $w_\tau < w_t < \bar{\eta}$; for $\alpha = 0$ and $w_\tau < E[w_\tau | f_t]$, we have that $w_\tau < E[w_\tau | f_t] < E[w_\tau | w_\tau \geq \bar{\eta}, f_t] < \bar{\eta}$.

[21] The estimates from the restricted sample potentially still underestimate the true effect of projection bias if customers are subject to the sunk cost fallacy (Arkes and Blumer, 1985).

5. Alternative Explanations and Robustness

In the previous section we have shown that projection bias can account for both, weather-dependent ticket orders and decisions to let pre-purchased tickets expire. In this section, we discuss plausible alternative explanations for these findings and the robustness of our results to different empirical specifications.

5.1. Is Current Weather Informative for Future Weather?

An immediate concern for our analysis so far is that individuals use current weather to update their beliefs about future weather conditions. There are two reasons why this could be optimal. First, current weather may be informative by itself such that consulting the weather forecast is unnecessary. Second, current weather may enhance the prediction of future weather, even given the weather forecast. This may be the case, for example, if the forecast cannot take regional factors into account sufficiently well.

We argue that the information content of current weather for future weather is, in general, limited if not nil due to large day to day fluctuations of local weather in Munich. In Figure 3, we plot average evening sunshine duration one to four days ahead (purged for seasonal effects by year and month dummies) against current sunshine duration. It turns out that tomorrow's sunshine hours are at best slightly positively related to today's sunshine duration. Furthermore, today's weather has no explanatory power for weather two or more days into the future.

In contrast, the weather forecast is able to explain future sunshine duration well. Figure 4 again plots average evening sunshine duration purged for seasonal effects as above, but this time against the forecast as given by forecast symbols. Evidently, there is a clear positive relationship between symbols indicating good future weather and realized sunshine duration.

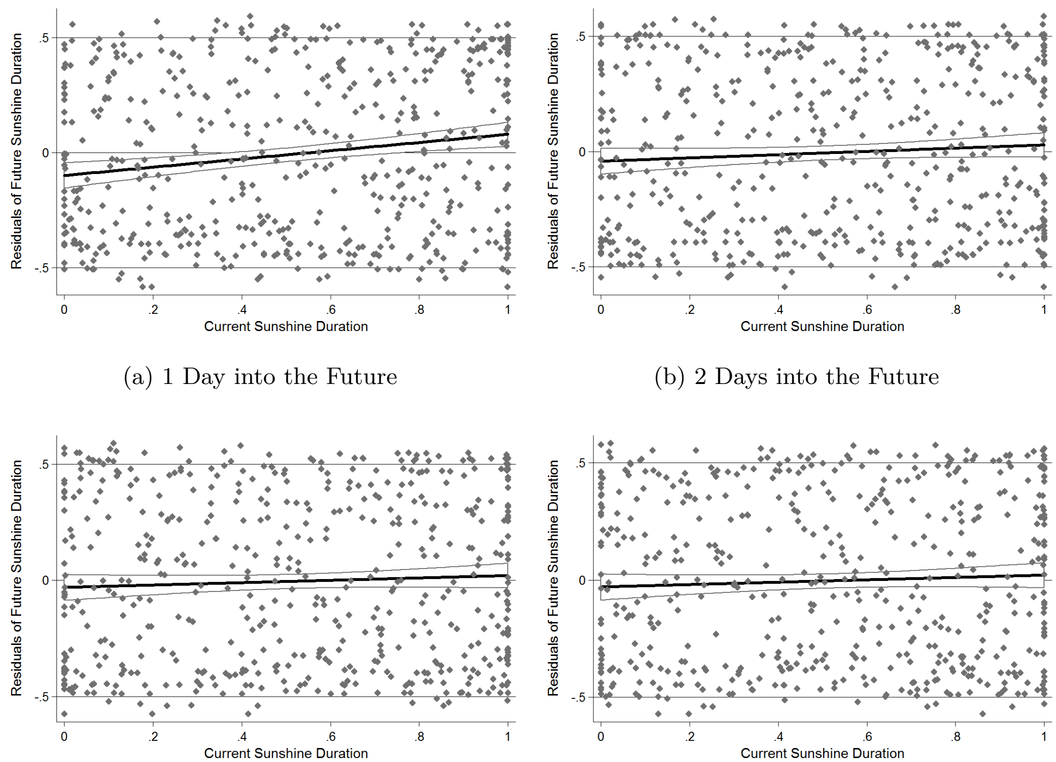
In order to reassure that the predictive power of current weather – even when not controlling for the forecast – is low, we complement the graphical analysis above with empirical estimates. In particular, we forecast evening sunshine duration S_h (as fraction of time) at a future date $h >$ t with the following model

$$S_h = \mathbf{W_t'}\gamma_\mathbf{W} + \mathbf{F_{ht}'}\gamma_\mathbf{F} + \mathbf{V_t'}\gamma_\mathbf{V} + \xi_{ht}, \tag{7}$$

where controls $\mathbf{V_t}$ include average sunshine duration and precipitation of the past two weeks before t as well as year and month dummies. Current weather $\mathbf{W_t}$ and forecast indicators $\mathbf{F_{ht}}$ are defined as above. We estimate model (7) for time horizons $h-t$ between one and four days with and without including the forecast $\mathbf{F_{ht}}$; the results are displayed in Table 9 in Appendix B. Confirming the graphical results, current weather seems to be uninformative for future weather. The exception of this rule is column (1) in Table 9 where the coefficients of current sunshine duration are statistically significant but economically small (a one percent increase in sunshine duration today leads to an increase in sunshine duration tomorrow of 0.14 percentage points on average). In contrast, the predictive power of the forecast is sizable; adding it to the model leads to a strong increase in

Figure 3: Predictive Power of Current Sunshine Duration

This figure provides a scatterplot of current sunshine duration against residuals of a regression of future evening sunshine duration (between 5 pm and 7 pm, 1 to 4 days into the future) on month and year dummy variables. The black solid line depicts the estimates of a regression of residuals on current sunshine duration, the grey lines depict the 95 percent confidence interval.



(a) 1 Day into the Future

(b) 2 Days into the Future

(c) 3 Days into the Future

(d) 4 Days into the Future

variance explained.[22]

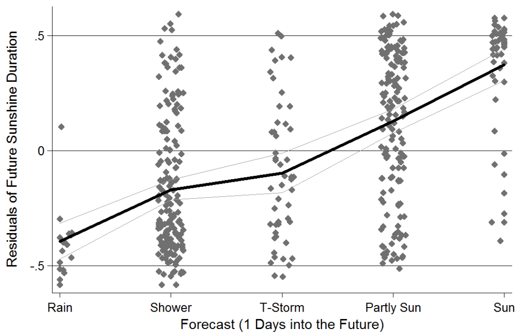
Survey results indicate that customers appreciate the predictive power of the weather forecast and consult the forecast frequently. From all respondents, 84 percent consult the weather forecast at least every other day or when they are planning weather related activities. Customers also appreciate the forecast's reliability: 85 (86) percent state that the forecast for tomorrow (two days ahead) will be correct in at least 80 (60) percent of cases. Hence, customers seem to have confidence in the forecast and utilize its information when making decisions. Moreover, because the availability of the forecast should help customers to make optimal decisions, it should diminish the impact of behavioral biases.

Our results indicate that it cannot be optimal for customers to interpret current weather as an informative signal for future weather. Hence, rational expectations cannot explain the weather-dependency of ticket orders outlined in Section 4. Even if the vast majority of customers are locals

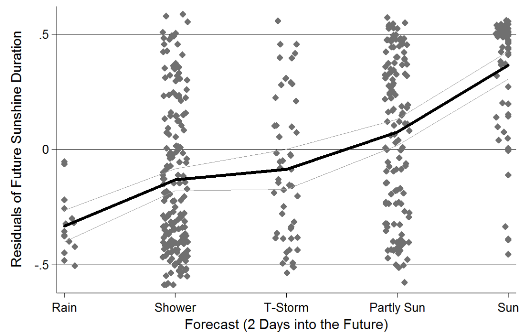
[22]Here, we assess the predictive power of current weather and the weather forecast for the main weather indicator of interest – sunshine duration – only. Repeating the exercise for precipitation and temperature gives similar results.

Figure 4: Predictive Power of the Weather Forecast

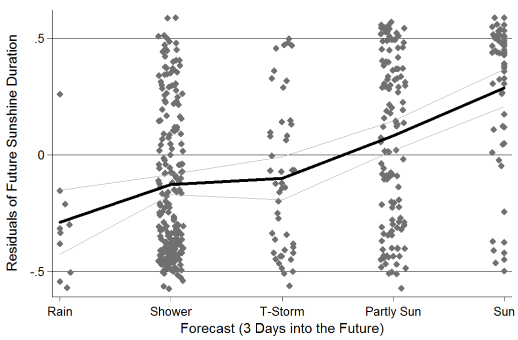
This figure provides a scatterplot of current forecast symbols against residuals of a regression of future evening sunshine duration (between 5 pm and 7 pm, 1 to 4 days into the future) on month and year dummy variables. To visualize the variation within a forecast category, random noise is added to the observations. The black solid line connects the means of the residuals conditional on the forecast, the grey lines connect the 95 percent confidence intervals of the conditional means.



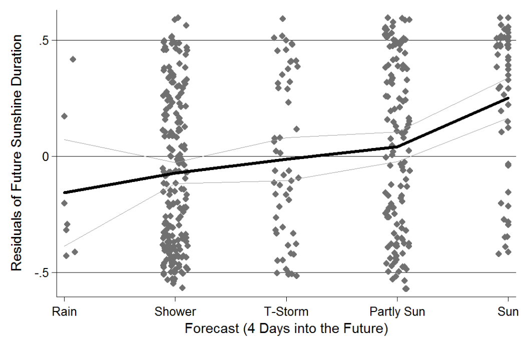
(a) 1 Day into the Future



(b) 2 Days into the Future



(c) 3 Days into the Future



(d) 4 Days into the Future

and hence familiar with local weather patterns, however, we cannot rule out the possibility that customers perceive current weather to be informative. If this were the case, the impact of purchase-date weather on ticket orders should decline for earlier orders. Yet, in Table 3 and in the analysis presented in the following subsection, we find that the correlation between purchase-date weather and ticket orders remains stable throughout different sales horizons.

5.2. Probability of Ticket Availability

Another concern is that due to capacity constraints higher ticket orders at any given point in time lead to a higher risk that the movie may sell out. Thus, if customers believe that the likelihood that tickets will be available on the movie-date decreases with good weather on the purchase-date, they have a higher incentive to buy on the purchase-date. Such a weather-dependent precautionary motive for buying tickets in advance would shift purchase decisions to earlier dates with good

Table 5: Effect of Purchase-Date Weather on Early Ticket Orders

	Normalized Ticket Orders			
	5 - 11 Days Out	9 - 15 Days Out	13 - 19 Days Out	17 - 23 Days Out
Avg. Sunshine Duration	0.36***	0.37**	0.38*	0.51**
	(0.13)	(0.16)	(0.20)	(0.20)
Avg. Rainfall per Hour	−0.17	0.23	−0.0079	−0.24
	(0.12)	(0.19)	(0.22)	(0.19)
Horizon Dummies	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3274	3254	3226	3184
Overall R^2	0.008	0.002	0.001	0.003

Notes: We report, for different sales horizons, the coefficients and standard errors (clustered on the movie-date level) from panel regressions of normalized daily ticket orders on purchase-date weather conditions (average sunshine duration as fraction of time, average rainfall per hour in mm) and dummies for the sales horizon. Fixed effects for the movie-date are included. Daily ticket orders for a particular movie-date are normalized by the mean of ticket orders conditional on the sales horizon. Coefficients are hence to be interpreted as increases in orders as a fraction of horizon-specific mean orders. Level of significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

weather, which could be a potential explanation for our results.

In fact, the movie theater in question is quite large (1,300 seats) and has hence been sold out only in 13 percent of evenings over the entire time span of our analysis. It has, however, so far never been sold out in advance. In general, customers seem to understand that they are always able to buy tickets online (until 6 pm on the movie-date): in the survey 88 percent of customers state that it is “unlikely” or “very unlikely” that all tickets for tomorrow’s screening will be sold out in advance.

Some customers may nevertheless perceive the probability of ticket availability to depend on current weather few days before the show.[23] However, deferring the purchase decision to a later date should perceived to be riskless for particularly early purchase-dates, for instance five days in advance and earlier. Thus, if customers’ concerns that the theater may sell out were the sole explanation for the effect of current weather on ticket orders, particularly early orders should be unaffected by purchase-date weather. In contrast, if our results can be explained by projection bias (or a reminder-effect of good weather), we expect to find an effect on early orders as well.

To analyze this prediction, we estimate the fixed effects model (4) for separate sets of advance orders which are defined by how many days in advance tickets were sold. More precisely, we estimate the effect of weather on ticket orders between 5 and 11 days in advance. Since weather forecasts for this time horizon are lacking, we cannot include the term $\mathbf{F}_{\tau\mathbf{t}}\beta_{\mathbf{F}}$ in these regressions. We repeat this exercise for time spans between 9 and 15, 13 and 19, and 17 and 23 days in advance.[24]

[23]Note that experienced customers should be less prone to hold such erroneous beliefs. That their orders are also driven by current weather (Table 8) hence alleviates this concern to some extent already.

[24]The choice of beginning and end days of these time-spans is obviously arbitrary. However, our qualitative results do not depend on the specific definition of these time spans as long as they are sufficiently long (greater than five days) to allow for enough within variation of early sales.

Table 6: Effect of Hourly Changes in Weather on Changes in Ticket Orders

	Differences in Hourly Ticket Orders		
	Daytime	Morning	Afternoon
Hourly Difference in Sunshine	0.039**	0.044	0.044*
	(0.018)	(0.029)	(0.024)
Hourly Difference in Rainfall	0.00068	−0.0021	0.00078
	(0.0038)	(0.0042)	(0.0048)
Hour Dummies	*Yes*	*Yes*	*Yes*
Horizon Dummies	*Yes*	*Yes*	*Yes*
Observations	21506	8600	10755
Adjusted R^2	0.001	0.001	0.001

Notes: We report the coefficients and robust standard errors of OLS regressions of the first difference of hourly ticket orders (1 to 4 days in advance) on the first difference of hourly purchase-date sunshine duration (as fraction of time), the difference in purchase-date rainfall (in mm), and hour as well as horizon dummies. Column 1 reports coefficients for all orders between 8 am and 8 pm. In the two remaining columns we split the dataset into orders before and after 2 pm. Level of Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 reports the results. It becomes apparent that the effect of average sunshine duration on orders is significantly greater than zero at least at the ten percent level for all estimated models. Most notably, the effect of weather on sales seems to be fairly constant over time, as the estimated parameters of current sunshine duration for early orders in Table 5 are in a very similar range as the estimates in Table 3 for orders up to four days in advance. This is consistent with projection bias driving the results.

Another instance in which changes in weather can naturally be assumed to have little impact on the probability of ticket availability are variations in weather from one hour to the next. Again, we only expect to find an effect of hourly changes in weather on changes in ticket orders if the state of the world by itself – and not its effect on market interactions – affects choice behavior.

To test this prediction, we regress, for a given movie-date, the first difference of ticket orders per hour on the first difference of hourly sunshine duration and precipitation. In addition, sales horizon and hour dummies are included as independent variables to control for different sales volumes depending on the number days tickes are purchased in advance and the time of the day, respectively. We restrict the sample to hours with potentially positive sunshine duration (8 am to 8 pm) as well as to hours in the morning (8 am to 2 pm) and afternoon (2 pm to 8pm) between one and four days ahead of the movie-date.

In this analysis, the effect of weather on ticket orders is identified through variations in weather within a given day. Given the low within-day variation in sales and thus low mean differences as dependent variable, the estimated coefficients are rather small (see Table 6). Still, hourly changes in weather have a statistically significant effect on changes in ticket orders. The estimates seem to be mainly driven by sales in the afternoon when most tickets are ordered and therefore hourly variation in sales is highest.

In light of the evidence that both, very early ticket orders as well as hourly changes in orders, are affected by current weather, we conclude that current weather explains ticket orders for which the probability of ticket availability is independent of purchase-date weather. Summarizing our above arguments, projection bias is the only explanation that can simultaneously account for all our empirical findings.

5.3. Selection and Robustness

Selection A third concern could be that we are studying a selected sample of customers who are particularly prone to make biased decisions. After all, given that online tickets have (so far) always been available on the movie-date it should, in most cases, be suboptimal to buy tickets in advance. Because we do not observe the process that leads to the selection of the sample of customers, we are not able to rule out this concern entirely. However, before we present evidence that deals with this possible confound, it should be noted that we are studying the behavior of a significant fraction (10 percent) of customers such that their behavior is interesting in itself.

To gauge whether selection is likely to be an issue for our results, we analyze the effect of purchase-date weather on ticket orders in sub-samples that are "artificially" selected according to various criteria. This helps us to assess whether decisions of different sets of customers are affected differentially by current weather. If this were the case, selection would certainly be a serious concern.

Table 7 reports the coefficient of purchase-date sunshine duration from the fixed effects model (4) for selected samples of ticket orders. First, note that all estimated coefficients are in a similar range as the baseline estimate from the first column of Table 3. In particular, this holds for the selected sample of repeat customers, who have displayed optimal behavior previously at least once by purchasing online tickets on the movie-date. This finding somewhat alleviates our concern that our results are merely driven by a selected sample of individuals particularly prone to behavioral biases.

Second, the magnitudes of coefficients follow patterns consistent with projection bias. The effect of average daily sunshine duration on ticket orders is larger during the daytime (before 8 pm) than at night; this is intuitive as current weather is particularly salient during the day. Furthermore, ticket orders comprising of more tickets are generally less affected by purchase-date weather than ticket orders of small parties. This should be expected if joint decision making reduces the impact of behavioral biases. And finally, purchase-date weather has a similar impact on ticket orders across movie-days (working days or weekend), movie genres, and the age of customers.

Robustness We conducted a number of additional robustness checks the results of which are extremely similar to our findings so far. In the interest of brevity we therefore report the results only verbally.

We examine the robustness of all empirical results to the inclusion and exclusion of various control variables in the cross section specification (5). First, we control for the popularity of the movie by including either the number of theaters in which the movie was shown on the opening weekend in

Table 7: Effect of Purchase-Date Sunshine Duration on Selected Samples of Ticket Orders

Selection Criterion for Ticket Orders	Coefficient of Avg. Sunshine	SE	N
Baseline (all orders; see Table 3)	0.49***	0.11	1554
Previous Purchase on Movie-Date	0.44**	0.20	1554
Time of Purchase			
Daytime (7 am - 8 pm)	0.52***	0.13	1554
Night (after 8 pm)	0.39**	0.17	1554
Weekday of the Movie-Date			
Weekend (Friday - Sunday)	0.40***	0.12	749
Working Day (Monday - Thursday)	0.53***	0.18	805
Number of Tickets			
1 Ticket	0.70***	0.27	1554
2 Tickets	0.50***	0.12	1554
more than 2 Tickets	0.39**	0.18	1554
Movie Genre			
Drama	0.48***	0.18	531
Comedy	0.43**	0.18	725
Age of Customer			
Below the Median (31 Years)	0.43***	0.14	1554
Above the Median (31 Years)	0.54***	0.12	1554

Notes: We report the coefficient and standard error (clustered on the movie-date level) of average purchase-date sunshine duration from panel regressions of model (4). In each row we use a different sub-sample of ticket orders to calculate daily normalized ticket orders (the dependent variable). For example, in the second row a ticket order is only considered if the customer placed at least one previous order on the movie-date. In the third row, an order is only considered if it was placed between 7 am and 8 pm; and so on. For each selected sub-sample of orders, normalized ticket orders are calculated by dividing the aggregate number of selected orders on a purchase-date for a given movie-date by the mean number of selected orders conditional on the sales horizon. Other independent variables (purchase-date weather and forecast variables as well as sales horizon dummies and movie-date fixed effects) are included in the regressions, but their coefficients are not reported in the table. These variables are defined in Section 3.2 and the description of Table 3. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Germany, or movie gross in Germany on the opening weekend (or both) as independent variables.[25] As movies are scheduled months in advance, their popularity is uncorrelated with actual weather such that it should come as no surprise that including popularity controls does not alter the results. Second, we attempt to proxy for the probability of ticket availability directly by (a) including a dummy indicating whether the theater turned out to sell out for the particular show of interest and (b) including the number of ticket orders until the purchase-date. Third, we check whether recent rather than current weather drives ticket orders by including one period lagged weather indicators in our model specifications. Finally, we exclude the controls $\mathbf{D_{\tau t}}$ and $\mathbf{X_{\tau t}}$, respectively, in all the

[25] The choice of the popularity indicator is somewhat arbitrary; for example, we could have chosen the total gross of the movie shown as well. We opted for opening weekend measures to avoid measurement error due to the total time the particular movie has been screened in theaters. The concern for measurement error arises, because the outdoor movie theater in question shows recent films as well as classics. All data for this analysis have been retrieved from the database http://www.boxofficemojo.com [October 2011].

models we estimate. Neither of these modifications leads to meaningful changes in the relationship between purchase-date weather and ticket orders.

In addition, we check whether our results are driven by the choice of using of average sunshine duration as the relevant weather variable. To do so, we substitute average sunshine duration by average temperature in all regressions with ticket orders as the dependent variable. By and large, this substitution leaves the results unchanged. Similarly, we test whether our conclusions are sensitive to the choice of the dependent variable. Instead of using aggregated ticket orders as the quantity to be explained, we could have also used the overall number of tickets sold as dependent variable. These two measures are highly correlated, such that it is not surprising that this modification does not lead to different conclusions.

Finally and as mentioned in Section 3.2, we further check whether our results depend on the choice of linear regressions to estimate the equations (4) and (5). To do so, we estimated those models – with ticket orders instead of normalized ticket orders as the dependent variables – using count data techniques (Poisson and negative binomial regressions with fixed effects if appropriate). This yields estimates that are extremely similar to the ones of the linear regressions such that our results are insensitive to the estimation techniques used.

6. Conclusion

There is a growing literature which shows that projection bias impedes the ability of individuals to correctly predict future utility. Predicted utility at unknown future states of the world tends to be biased towards utility at today's state of the world.

This paper contributes to the literature by showing that individual decisions are affected by projection bias even in a choice problem in which utility is particularly state-dependent and where the transient nature of the current state is obvious and explicitly pointed out to decision makers. Because in such a situation decision makers should be attentive to predicting their state-dependent utility correctly, we expect to find a minimal influence of projection bias on decisions. Yet, we find that the current state influences choices to a large extent nevertheless, which suggests that de-biasing decision makers may be challenging.

Given that we find projection bias to have profound influence even on a simple decision, a promising avenue for future research could be to study potential aggregate implications of the bias. Projection bias can generate aggregate effects because individuals who observe the same state of the world make choices that are biased in the same direction. For example, projection bias can potentially have business cycle implications as it suggests that people oversave in downturns when the utility of having past savings at disposal is high, and undersave in booms.

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Appendix

A. Proofs

A.1. Proof of Lemma 1

We begin the proof by making two observations. First, it is easy to see that $F^R(f_t, \eta)$ is strictly decreasing and convex in η due to strict concavity of $u(\cdot)$. Hence, the fixed point $\tilde{\eta}$ satisfying $F^R(f_t, \tilde{\eta}) = 0$, which exists by assumption 1 (i) is unique. Second, note that for all $\eta > w_t$ we have that

$$F^P(f_t, w_t, \eta) < (1 - H(\eta)) \Big((1-\alpha)\, E[u(w_\tau) |\, w_\tau \geq \eta, f_t] + \alpha u(\eta) - u(\eta) \Big) - c \leq F^R(f_t, \eta),$$

since $E[u(w_\tau) |\, w_\tau \geq \eta, f_t] \geq u(\eta)$. Thus, for large η, $F^R(\cdot)$ is an upper bound for $F^P(\cdot)$, where the former is smaller than zero for $\eta > \tilde{\eta}$.

Now, note that there always exists a fixed point $\bar{\eta}$ for which $F^P(f_t, w_t, \bar{\eta}) = 0$. To see this, consider the cases $\alpha = 0$ and $\alpha = 1$. For $\alpha = 0$, $F^P(f_t, w_t, \eta_t) = F^R(f_t, \eta_t)$ and by assumption 1 (i) there always exists η' satisfying $F^R(f_t, \eta') = 0$. For $\alpha = 1$, $F^P(f_t, w_t, \eta) = (1 - H(\eta))\, (u(w_t) - u(\eta)) - c$, which equals zero for some $\eta'' < w_t$ due to the strict concavity of $u(\cdot)$. Hence, some $\bar{\eta} \in [\eta', \eta'']$ satisfies $F^P(f_t, w_t, \bar{\eta}) = 0$ for $\alpha \in (0,1)$.

Finally, we need to show that $\bar{\eta}$ is unique. Because $F^R(\cdot)$ is an upper bound for $F^P(\cdot)$ for large η, it is sufficient to show that $F^P(\cdot)$ is quasi-convex in η. The first and second derivatives of $F^P(\cdot)$ with respect to η are

$$\frac{\partial F^P(f_t, w_t, \eta)}{\partial \eta} = \alpha h(\eta)\, (u(\eta) - u(w_t)) - (1 - H(\eta))\, u'(\eta)$$

and

$$\frac{\partial^2 F^P(f_t, w_t, \eta)}{\partial \eta^2} = \alpha h'(\eta)\, (u(\eta) - u(w_t)) + (1+\alpha) h(\eta) u'(\eta) - (1 - H(\eta))\, u''(\eta).$$

Hence, if there is some $\hat{\eta}$ with $\partial F^P(f_t, w_t, \hat{\eta})/\partial \eta = 0$, we have

$$\frac{\partial^2 F^P(f_t, w_t, \hat{\eta})}{\partial \eta^2} = \frac{(1 - H(\hat{\eta}))\, h'(\hat{\eta}) + h(\hat{\eta})^2}{h(\hat{\eta})} u'(\hat{\eta}) + \alpha h(\hat{\eta}) u'(\hat{\eta}) - (1 - H(\hat{\eta}))\, u''(\hat{\eta}) > 0,$$

since $(1 - H(\hat{\eta}))\, h'(\hat{\eta}) + h(\hat{\eta})^2 \geq 0$ by assumption 1 (ii). This completes the proof. $\square$

A.2. Proof of Hypothesis 1

Clearly, $\partial y / \partial w_t > 0$ if either $\partial n(w_t)/\partial w_t > 0$ or $\partial \bar{\eta}/\partial w_t > 0$. Iff $\alpha > 0$, $\partial \bar{\eta}/\partial w_t > 0$ follows directly from application of the implicit function theorem on (2). $\square$

A.3. Proof of Hypothesis 2

Obvious, following the same argument as in the proof of Hypothesis 1. $\square$

B. Tables

Table 8: Effect of Purchase-Date Weather on Ticket Orders for Repeat Customers

	Normalized Ticket Orders by Subsets of Customers		
	Repeat Customers	Repeat Customers within One Season	Repeat Customers with Bad Experience
Avg. Sunshine Duration	0.51***	0.70***	0.81***
	(0.13)	(0.16)	(0.24)
Avg. Rainfall per Hour	−0.23	0.0098	0.36
	(0.22)	(0.25)	(0.39)
Forecast	*Yes*	*Yes*	*Yes*
Horizon Dummies	*Yes*	*Yes*	*Yes*
Observations	1554	1554	1554
Overall R^2	0.04	0.05	0.00

Notes: We report the coefficients and standard errors (clustered on the movie-date level) from panel regressions of model (4). In each column we use a different sub-sample of ticket orders to calculate daily normalized ticket orders (the dependent variable). These criteria are related to the level of the customer's experience with visiting the cinema. In the first (second) column, an order is only considered if it is not the customer's first order (not the customer's first order in the current season). In the third column, an order is only considered if it is not the customer's first order and the customer had previously placed an order for a movie-date at which there was rainfall during the show. For each selected sub-sample of orders, normalized ticket orders are calculated by dividing the aggregate number of selected orders on a purchase-date for a given movie-date by the mean number of selected orders conditional on the sales horizon. Coefficients are hence to be interpreted as increases in selected orders as a fraction of horizon-specific mean selected orders. Independent variables (purchase-date weather and forecast variables as well as sales horizon dummies and movie-date fixed effects) are defined in Section 3.2 and the description of Table 3. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Predictive Power of Current Weather and the Weather Forecast

	Evening Sunshine Duration							
	1 Day into the Future		2 Days into the Future		3 Days into the Future		4 Days into the Future	
Avg. Sunshine Duration	0.143***	−0.006	0.017	−0.010	−0.009	−0.054	0.022	0.039
	(0.051)	(0.053)	(0.051)	(0.051)	(0.052)	(0.051)	(0.052)	(0.054)
Avg. Rainfall per Hour	−0.066	0.087	−0.060	−0.003	−0.080	−0.067	−0.012	−0.048
	(0.067)	(0.070)	(0.068)	(0.074)	(0.068)	(0.076)	(0.068)	(0.079)
Forecasted Maxtemp.		0.017***		0.009		0.013*		0.012*
		(0.006)		(0.007)		(0.007)		(0.007)
Forecasted Mintemp.		−0.007		−0.001		0.001		−0.002
		(0.008)		(0.009)		(0.009)		(0.009)
Symbol Partly Sunny		−0.224***		−0.296***		−0.194***		−0.196***
		(0.049)		(0.050)		(0.055)		(0.057)
Symbol T-Storm		−0.450***		−0.446***		−0.391***		−0.251***
		(0.060)		(0.063)		(0.067)		(0.068)
Symbol Shower		−0.489***		−0.476***		−0.368***		−0.277***
		(0.051)		(0.054)		(0.055)		(0.057)
Symbol Rain		−0.681***		−0.638***		−0.492***		−0.383**
		(0.095)		(0.104)		(0.120)		(0.158)
MA Rain 14 days	−0.172	−0.210	0.013	0.140	−0.182	0.081	−0.347	−0.065
	(0.291)	(0.266)	(0.293)	(0.281)	(0.294)	(0.292)	(0.294)	(0.299)
MA Sun 14 days	0.211*	0.004	0.279**	0.117	0.227**	0.152	0.140	0.107
	(0.110)	(0.101)	(0.111)	(0.106)	(0.112)	(0.111)	(0.112)	(0.116)
Constant	0.416***	0.596***	0.444***	0.686***	0.483***	0.483***	0.508***	0.433***
	(0.084)	(0.139)	(0.085)	(0.153)	(0.086)	(0.151)	(0.086)	(0.158)
Year & Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	544	448	542	447	540	447	538	447
Adjusted R^2	0.057	0.344	0.030	0.270	0.023	0.210	0.024	0.108

Notes: We report the coefficients and robust standard errors of OLS regressions analyzing which variables are able to predict future sunshine duration between 5 pm and 7 pm, 1 to 4 days into the future (the dependent variable). Candidate predictors (the independent variables) are current weather conditions (average sunshine duration as fraction of time, average hourly rainfall in mm), the current weather forecast (forecasted temperature and weather symbols; only in every other column), current weather trends (sunshine duration and rainfall in the past fortnight), as well as year and month dummies. Level of Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C. Picture

Figure 5: Location of the Theater

This picture shows the location of the theater. Visitors are sitting in the amphitheater on different rows on flaggings or on wooden boards (the area at the bottom left corner of the picture). The screen is on the left of this picture (not shown).