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# WEATHER TO GO TO COLLEGE

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Does current utility bias predictions of future utility for high stakes decisions? Here I provide field evidence consistent with such Projection Bias in one of life's most thought-about decisions: college enrolment. After arguing and documenting with survey evidence that cloudiness increases the appeal of academic activities, I analyse the enrolment decisions of 1,284 prospective students who visited a university known for its academic strengths and recreational weaknesses. Consistent with the notion that *current* weather conditions influence decisions about *future* academic activities, I find that an increase in cloudcover of one standard deviation on the day of the visit is associated with an increase in the probability of enrolment of 9 percentage points.

When making decisions about future consumption, people must make predictions about the utility they will derive from it. While economic theory typically assumes away any difficulty in making such predictions, abundant empirical work has shown that predicting future utility is actually quite difficult; for a review see Loewenstein and Schkade (1999). A particularly robust finding in this literature is that people tend to bias their estimates of future utility towards their current utility, a phenomenon labelled Projection Bias by Loewenstein *et al.* (2003). While it is sensible to base predictions about the future on the present, Projection Bias is a *bias* because predictions of future utility are systematically off in the direction of current utility, i.e. they are predictably wrong.

In general, Projection Bias will lead to systematic errors when decisions are made in the presence of factors that influence current but not future utility. Prior research, for example, has shown that grocery shoppers buy more items if shopping while hungry (Gilbert *et al.*, 2002), that current arousal influences predictions about future sexual behaviour (Ariely and Loewenstein, 2006) and that catalogue orders for winter clothing are more likely to be returned if ordered on colder days (Conlin *et al.*, 2007).

As with all deviations from rationality, an important question regarding biases in the prediction of future utility is whether they play a role in high stakes decisions – when people are highly motivated to 'getting it right' – or whether they are only present in hypothetical and low-stake decisions.

This article provides evidence consistent with Projection Bias playing a role in one of life's most thought-about decisions: which college to enrol in. Although college enrolment decisions are made during a long period of time and hence identifying the *current* utility which could potentially contaminate predictions about future utility is difficult, one aspect of the college decision process lends itself particularly well to studying projection bias: college visits.

Many college applicants visit the schools they are applying to prior to making enrolment decisions, providing a specific instance in which a particular experienced utility (that enjoyed during the visit) may influence predicted future utility (that to be enjoyed from attending the visited school over several years). Importantly, if visitors fall prey to Projection Bias, then transient factors that influence the utility that would be experienced if the prospective student belonged to the visited university on *the day of the visit* will influence the predicted utility of belonging to such institution in the future.

For example, prospective students visiting a school well known for its party life would have a more positive assessment of the utility associated with attending that school if they visited it, say, on a Friday after having worked hard during the preceding week. Because partying *that day* would be particularly appealing, the projected utility of being able to do so often during the next four years would probably be exaggerated.

For a school whose forte was academic, on the other hand, transient factors that made engaging in academic activities more appealing on the day of the visit would increase the predicted utility of engaging in those activities in the future and hence possibly increase enrolment rates.

One factor likely to influence the appeal of engaging in academic activities is the weather. Intuition and survey evidence presented in Section 2 suggest that cloudy weather, probably due to the sadder mood it induces and the reduced opportunity cost of outdoor activities it creates, is more inviting to academic activities than sunny weather is. Visitors of an academically demanding institution, then, may be more prone to enrolling in such an institution after visiting it on a cloudier day, since academic work would have seemed more inviting during their visit and hence been projected as more inviting into the future as well.[1]

In this article I test this prediction, analysing enrolment decisions of 1,284 prospective college students who visited a university well known for its extremely challenging academic environment.[2] Consistent with the logic put forward above, I find that cloudiness during visits has a statistically and practically significant impact on enrolment rates: an increase in cloudiness of one standard deviation on the day of a visit is associated with an increase in the enrolment probability of around 9 percentage points.

Adding controls for average weather conditions for the calendar date of the visit and month dummies leaves the results unchanged, ruling out the possibility that this pattern arises as a result of a time-of-year confound. Employing the admission rather than the enrolment decision as the dependent variable, there is no impact of cloudcover, suggesting the pattern is not due to self-selection into interviews as a function of weather on the day of the visit.

There is an important difference between the main finding of this article and existing studies documenting Projection Bias. Considering that visitors are probably not deciding whether to enrol in the visited school *during* their visit, cloudiness must be influencing college decisions through memory. Notably, visitors are influenced by an incidental factor which is no longer present at the time they are making a decision.

[1] Note that in order for cloudiness to increase enrolment rates it is not necessary for the visited school to be the academically strongest option in the applicant's choice set, as would be the case if assessing the impact of cloudcover experienced during the day in which applicants make final enrollment decisions. Because here I study the impact of cloudcover during a school visit, a much weaker condition is required, simply that the visited school's academic attributes be more favorable than its non-academic ones, such that greater cloudiness during the visit increases the appeal of the university's forte.

[2] Although the identity of the school that facilitated the enrolment data cannot be disclosed, it is informative that a recent college guide describes it with 'sleep, friends, work, choose two', and that online reviews by its alumni include in its pros: 'strong education', 'great professional concentration' and 'terrific academics' and its cons 'socialising [is] difficult' and 'get[s] boring').

Rather than projecting current utility, people appear to be projecting their remembered utility.

Such a process is consistent with the findings from the seminal paper by Dutton and Aron (1974), where men who met a woman in a situation of high arousal (after having just crossed a suspension bridge) were more likely to call her, *at a future time*, than those who met her in a situation of normal arousal (at least 10 minutes after having crossed that same bridge). In relation to the classical example of shopping on an empty stomach, these results are equivalent to demonstrating that foods *tasted for the first time* on an empty stomach are remembered as more enjoyable and might hence be disproportionately likely to be purchased again.

The remainder of the article is organised as follows: Section 1 presents survey evidence consistent with cloudy weather increasing the appeal of academic activities, Section 2 reports the results from the visits and enrolment data and Section 3 concludes.

## 1. Cloudiness and Academics

Academic related activities and goods are likely to be more appealing under cloudier weather for at least two reasons. First, cloudiness induces sad moods (Cunningham, 1979; Hirshleifer and Shumway, 2003; Rind, 1996), making mellow activities like reading or studying more appealing. Secondly, sunny weather increases the appeal of outdoor activities like practising sports or hiking, increasing the opportunity cost of engaging in academic activities.

To assess the validity of the hypothesised link between current cloudiness and the appeal of academic activities empirically I included two questions in separate surveys carried out at an Ivy League University. The first directly asked people to reveal whether they find studying more appealing on cloudy or sunny days and the second asked a different set of respondents to indicate on which of two days, a cloudy or a sunny one, they would prefer to complete a 4-hour long school assignment.

In particular, the question inserted into one survey was ($N = 37$): Recent studies show that some people find it more appealing to study and do homework on cloudy days while others find it more appealing on sunny days. In your personal experience, when do you find school work more appealing (or less aversive)?

Figure 1 shows the distribution of answers to this question (on a 1–7 scale, where 1 is definitely more appealing on sunny days and 7 is definitely more appealing on sunny days). The results are consistent with cloudiness increasing the marginal utility of studying; the average answer was $M = 5.13$, significantly greater than the neutral answer of four ($t(36) = 4.13$, $p = 0.0002$). Similarly, the majority of respondents, 78%, chose a number greater than four compared to just 14% choosing a number smaller than four.

The question inserted into the other survey ($N = 137$) was: Suppose you have a project due for class which would take 4 hours of work (including reading from books, writing quick summaries and searching for information on the internet), and you can do it either tomorrow or the day after tomorrow. In making the decision, consider that [*tomorrow/the day after tomorrow*] is forecast to be a dark cloudy day, and [*the day after tomorrow/tomorrow*] a bright and sunny one.

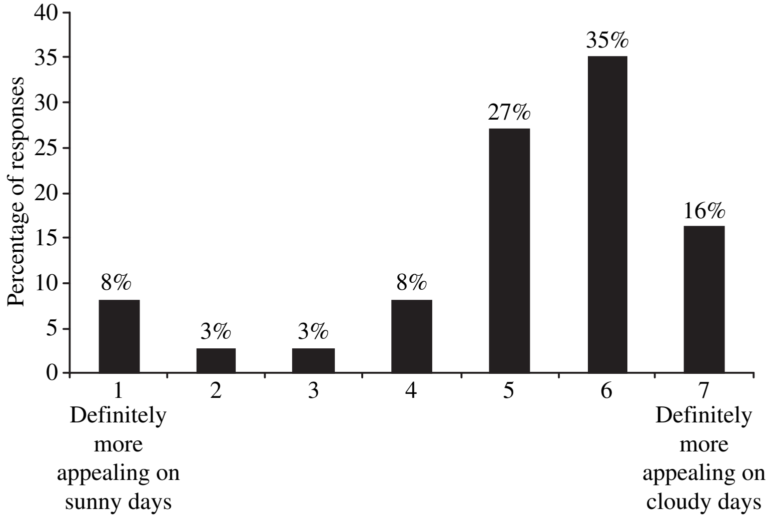


Fig. 1. *Distribution of Answers from Student Survey* ($N = 37$) *to Question 'Do you find it more appealing to study on cloudy or sunny days'?*

On which of the two days you think you would prefer to do the work? (Subjects responded using a 1–10 scale where 1 is Definitely Tomorrow and 10 is Definitely Day After Tomorrow.)

Half the subjects were asked to imagine 'tomorrow' would be sunny and 'the day after' cloudy, and half the subjects were asked to imagine the opposite. The distribution of answers is reported in Figure 2.

Respondents expressed a clear preference for completing the work 'tomorrow' when 'tomorrow' was going to be a cloudy day ($M = 2.9$) but the reversed preference was obtained when 'tomorrow' was going to be a sunny day ($M = 6.4$), $t(151) = 9.08$, $p < 0.0001$.[3] Similarly, 33% of subjects in the 'cloudy tomorrow' condition chose '1-Definitely tomorrow' compared to just 9% in the 'sunny tomorrow' condition, a statistically significant difference $\chi^2 = 13.1$, $p = 0.0003$. The survey evidence, therefore, strongly suggests that current cloudiness increases the (relative) marginal utility of studying. Additional evidence of a complementarity between cloudiness and taste for academic 'goods' comes from a recent paper where I analyse admission decisions made by university admission reviewers, finding that reviewers accept academically stronger candidates when reviewing applications on cloudier rather than sunnier days (Simonsohn, 2007).

## 2. College Visits Data

### 2.1. *Visits Data*

The college visits data was provided by the admissions office of a private university in the northeastern US, which is, as mentioned in the Introduction, well known for its

[3] The difference is also significant at the 0.0001 level in a non-parametric sign test.

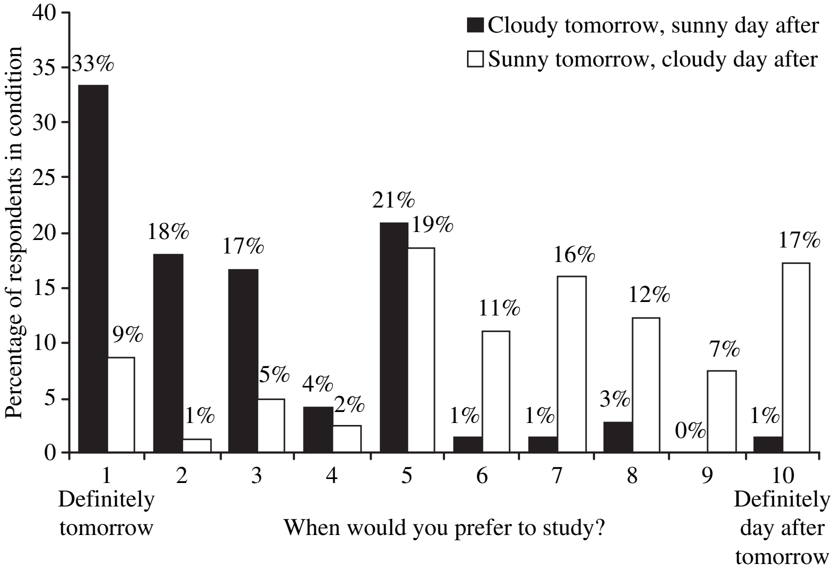


Fig. 2. *Distribution of Answers from Student Survey* ($N = 137$) *Asking Students to Decide Whether to Conduct 4 Hours of School-work* 'tomorrow' *or* 'the day after tomorrow', *Randomly Varying Which of the Two Days Would be Sunny or Cloudy*

academic strengths and recreational weaknesses. The dataset consists of the university's records of 1,284 interviews with undergraduate applicants. Interviews are conducted by an admission specialist from the university and are designed primarily to help students learn more about the school they are applying to. They are voluntary and are not part of the admission process *per se*. Students typically sign up for interviews ahead of time, combining them with a campus visit.

The dataset includes information on the date of the campus visit, whether the applicant was admitted to the university, and (conditional on being accepted) whether s/he chose to enrol or not. In total the dataset contains information on 1,284 visitors, 562 of which (44%) were admitted, 259 of which (46%) enrolled. Not surprisingly, given the self-selection involved in deciding to visit campus, both of these rates are higher than those for the full pool of applicants.

### 2.2. *Weather Data*

Weather data on temperature, wind speed, precipitation and cloudcover were obtained from the National Oceanic and Atmospheric Administration's (NOAA) website for the academic year for which the visits data are available and for the preceding 5 years. The historical weather data were used to construct average weather conditions for each calendar date of the year, providing useful time-of-year controls.

Although all weather variables just listed are utilised in the analyses that follow, the variable of primary interest is cloudcover and hence it is useful to provide some additional information on it. Cloudcover is measured, in the weather station of the city

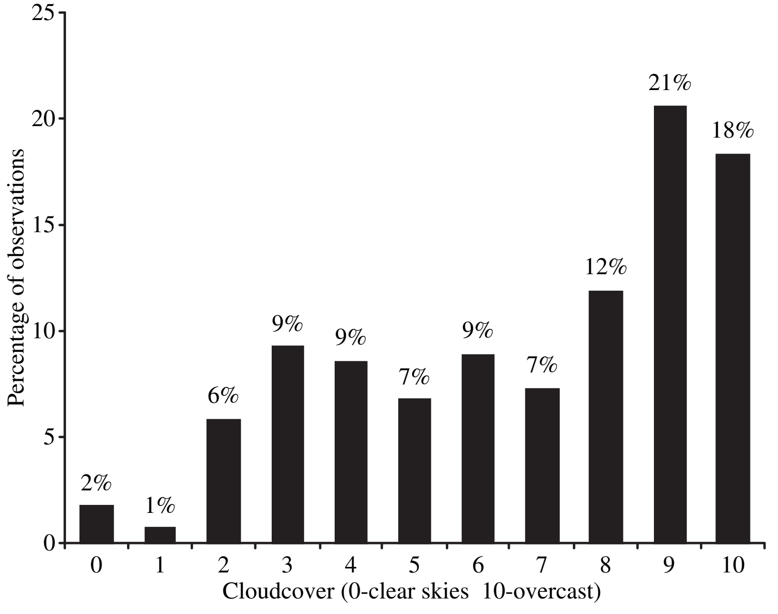


Fig. 3. *Distribution of Cloudcover Across Days Applicants in Sample Visited Campus* (Each visit (rather than calendar date) is an Observation)

of interest, on a discrete 0-*clear skies* to 10-*complete overcast* scale.[4] Figure 3 shows a histogram with the relative frequencies of the 11 possible values, with visits (rather than calendar dates) as the unit of observation. It shows ample variation within the sample ($M = 6.77$, $SD = 2.79$).

An interesting feature of cloudcover is that it experiences significant short-term fluctuations. Table 1 shows correlations of cloudcover on day $t$ with cloudcover on days $t-1$, $t-2$ and $t-3$. Column (1) shows raw correlations and Column (2) partials out month fixed effects (i.e. it reports the correlations for residuals from regressions with month dummies as the only predictors of cloudcover). The Table shows that cloudcover varies sufficiently during short periods of time that the correlation between cloudcover today and cloudcover in 3 days is not statistically different from 0. When month fixed effects are partialled out, the correlation between cloudcover in $t$ and in $t-2$ is not statistically significant ($r = 0.02$). This already suggests that any association between cloudcover and enrolment is unlikely to be caused by a time-of-year confound.

### 2.3. *Regression Analyses*

To assess the impact of cloudcover during a visit on subsequent enrolment decisions, a linear probability model was estimated with visitors as the unit of observation,

[4] Other weather stations, and this weather station in previous years, measure cloudcover as the percentage of all daylight minutes in the day in which there was sunshine.

Table 1

*Correlations of Cloudover (0–10 scale) Across Proximate Days*

| | Raw correlations with cloudcover on day $t$ | Correlations with cloudcover on day $t$ net of month fixed effects |
|---|---|---|
| Cloudcover on day $t$ | 1 | 1 |
| Cloudcover on day $t-1$ | 0.41*** | 0.36*** |
| Cloudcover on day $t-2$ | 0.10** | 0.02 |
| Cloudcover on day $t-3$ | 0.05 | −0.04 |

Table reports correlations in cloudcover across proximate days (cloudcover is measured in a discrete 0–10 scale by the local weather station). Column 1 reports raw correlations while column 2 partialing out monthly fixed effects.
*,**,*** indicates significance at the 10%, 5% and 1% level respectively

enrolment (1-yes, 0-no) as the dependent variable and all of the weather variables experienced during the visit as independent variables (neither qualitatively nor in significance do the results change if a logistic regression is estimated instead). Since counterfactual enrolment decisions by visitors who were not admitted are not observed, the sample is restricted to the 562 visitors who were admitted.

The results are presented on Table 2. Column 1 presents the baseline specification where only the key independent variable, cloudcover, is included in the regression. The point estimate is positive and significant at the 5% level. It indicates that in response to a one point change in cloudcover experienced during the college visit, the probability of enrolment, conditioning on acceptance, changes by around 1.8 percentage points.

Column 2 adds other weather variables for the day of the visit. None of them is statistically significant, and a joint test of all non-cloudcover variables equalling zero is not rejected ($p = 0.83$). Controlling for other weather variables the point estimate for cloudcover increases in both size and significance.

### 2.4. *Time-of-year as a Possible Confound*

Heterogeneity in *ex ante* likelihood of enrolling across visitors coming at different times of the year is the most plausible confound for the documented relationship between cloudcover and enrolment rates. The specifications reported in columns 3 and 4 of Table 2 attempt to address this time-of-year concern. In particular, Column 3 adds as controls average weather conditions for the calendar date of the visit from the five previous years. For example, when attempting to predict the enrolment decision of a visitor on October 15th of a given year, the regression controls not only for all other weather variables on that day but also for the average of all these variables, including cloudcover, on October 15th of the preceding 5 years. Column 3 also adds month dummies to further take into account any systematic time-of-year variation in enrolment probability.

Contrary to what would be expected in the presence of a time-of-year confound, the point estimate for cloudcover in column (3) increases slightly in both size and significance with respect to column (2). The point estimate from column (3) indicates than a change in cloudcover of one standard deviation is associated with a change in probability of enrolling, conditional on being accepted, of roughly 9 percentage points.

Table 2

*Impact of Cloudcover on Enrolment and Admission (OLS)*

| Dependent variable (1-yes, 0-no) | (1) Enrolled? Baseline | (2) Enrolled? Adds other weather variables | (3) Enrolled? Adds Average weather conditions | (4) Enrolled? Predicts with weather from two days *prior* to visit | (5) Admitted? Same as (3) but with admission decision as dependent variable |
|---|---|---|---|---|---|
| Intercept | 0.342*** | 0.180 | −0.013 | 0.407*** | 0.538** |
| | (0.055) | (0.164) | (0.353) | (0.137) | (0.210) |
| Cloud Cover on day of visit (0-clear skies to 10-overcast) | 0.018** | 0.027** | 0.032** | – | 0.004 |
| | (0.008) | (0.011) | (0.012) | – | (0.008) |
| Cloud Cover two days | – | – | – | 0.001 | – |
| prior to visit | – | – | – | (0.000) | – |
| Maximum Temperature (max) | – | 0.004 | 0.003 | 0.000 | 0.000 |
| | – | (0.004) | (0.004) | (0.004) | (0.003) |
| Minimum Temperature (min) | – | −0.002 | −0.005 | 0.001 | −0.002 |
| | – | (0.004) | (0.005) | (0.004) | (0.003) |
| Wind Speed (miles per hour) | – | −0.004 | −0.005 | 0.002 | −0.003 |
| | – | (0.003) | (0.004) | (0.004) | (0.002) |
| Rain precipitation (in inches) | – | −0.056 | −0.024 | −0.076 | 0.026 |
| | – | (0.091) | (0.119) | (0.144) | (0.078) |
| Snow precipitation (in inches) | – | 0.008 | 0.009 | 0.002 | 0.007 |
| | – | (0.008) | (0.009) | (0.008) | (0.006) |
| Average weather conditions for calendar date (DF = 6) | No | No | Yes | No | Yes |
| Month dummies | No | No | Yes | No | Yes |
| Number of Observations | 562 | 562 | 562 | 562 | 1,284 |
| $R^2$ | 0.0096 | 0.0146 | 0.0573 | 0.0018 | 0.0279 |

*Notes.* Table reports point estimates in linear probability models with college visitors as the unit of observation. In columns 1–4 the dependent variable equals 1 if the visitor enrolled and 0 if she did not. In column 5 the dependent variable equals 1 if the visitor was admitted and 0 otherwise. Standard errors reported below parameter estimates. Average weather conditions correspond to averages for each of the weather variables presented in the Table over the 5 preceding years.
*,**,*** Indicates significance at the 10%, 5% and 1% level respectively.

Column (4) takes an alternative approach for ruling out the time-of-year confound. It regresses enrolment decisions not on cloudcover on the day of the visit but on cloudcover two days prior to it. Any reasonable time-of-year confound story would predict a very similar effect for columns (4) and (3). The point estimate for cloudcover in column (4), however, is very small and not statistically significant, further suggesting it is actual cloudcover on the day of the visit rather than time-of-year proxied by such variable that is leading to the significant relationship that is documented.

### 2.5. *Self-selection into the Sample as Possible Confound*

A spurious relationship between cloudcover and enrolment could also be the result of the following selection bias: students' *ex ante* likelihood of enrolling in the visited school affects how they respond to weather conditions on the day of their interview and, in particular, students with lower inclination to enrol are less likely to show up for their interview on a bad-weather day. If this type of self-selection occurred, days of bad weather would over-represent enthusiastic students (because the dataset includes only students who show up for interviews) generating a spurious relationship between cloudcover and enrolment.

There are several reasons to doubt that such a process could be behind the results. First of all, the process itself seems implausible: although one may imagine that in the presence of extreme weather conditions (e.g. snowstorms or high winds) students may refrain from attending a pre-scheduled interview, it is unlikely that students would cancel appointments because the sky is 'too grey'. If weather correlates with enrolment rates because unenthusiastic students cancel appointments on bad weather days, temperature, wind and precipitation would be expected to be the strongest predictors of behaviour, not cloudcover.

To test this alternative explanation empirically, it would be desirable to obtain data on students who scheduled interviews and do not show up for them but such data are regrettably unavailable. Through personal conversations with the admissions office, however, I was assured that interviews are very rarely cancelled.

There are other predictions arising from the self-selection story that can be tested with the available data. One of them relies on the *admission* decision. If students who choose to attend an interview conditional on it being a cloudy day differ from those that do so on sunny days, cloudcover might predict whether a student is *admitted* to the university. To test this possibility column 5 in Table 2 reports the results from a linear probability model where admission (1-yes, 0-otherwise) is the dependent variable and weather conditions on the day of the *visit* were the explanatory ones. Neither cloudcover nor any other weather variable on the day of the visit correlate with the chances of being admitted (all p-values greater than 0.4). Furthermore, the joint test of all coefficients being zero, including cloudcover, cannot be rejected ($p = 0.54$).

Perhaps most tellingly, if cloudiness affects students' decisions to show up to their interview, total number of interviews per day and cloudcover should be correlated, yet they are not ($r = 0.04$, $p = 0.58$).

### 2.6. *Correlation with Cloudcover at Competing Universities*

The last concern I address is the plausibility and possible consequences of cloudcover being correlated across different schools visited by the same student. The fact that cloudcover within the same city has a correlation of 0 between two non-consecutive days (see Table 1) already suggests that a significant correlation in cloudcover across different schools is unlikely, as students would almost certainly visit different schools on different days. Once one considers that visitors differ in the set of schools they visit, in the order in which they visit them and in how much time they place between visits, it becomes virtually impossible that there might be a significant correlation between the cloudcover visitors to the school providing the data experienced and what they experienced in the other schools they visited (recall that the regressions partial out seasonal variation in cloudcover).

However implausible, it is worth considering the possible consequences of cloudcover being correlated across different schools. To this end consider a stylised linear decision model for student *i* deciding between schools *j* and *k*, where the probability of enrolling in school *j*, $E_{i,j}$, is a function of cloudcover experienced while visiting *j* and *k*, $C_{i,j}$ and $C_{i,k}$ respectively, as in:

$$E_{i,j} = a + bC_{i,j} + dC_{i,k} + \varepsilon_i.$$

If $C_{i,k}$ is not included in the regression, then $\mathrm{E}(\widehat{b})$ no longer equals *b*, but rather $\mathrm{E}(\widehat{b}) = b + d\ \mathrm{Cov}(C_{i,j}, C_{i,k})/\mathrm{Var}(C_{i,j})$. The sign of the bias in the estimation of *b* depends on the sign of *d* and of $\mathrm{Cov}(C_{i,j}, C_{i,k})$.

The most plausible sign for *d* is the opposite of *b*'s; if higher cloudcover in *j* increases enrolment into *j*, then it reduces enrolment into *k*. Since $\widehat{b} > 0$, *d* should be negative.

In terms of the correlation in cloudcover between cities; if contrary to the evidence from Table 1 $\mathrm{Cov}(C_{i,j}, C_{i,k}) \neq 0$, its most plausible sign is positive; schools visited by a given student over a short period of time will tend to be geographically close and hence affected by similar, rather than dissimilar, weather conditions over short periods of time. If as is argued here $d < 0$ and $\mathrm{Cov}(C_{i,j}, C_{i,k}) > 0$, the net effect of omitting $C_{i,k}$ from the regression would be to bias $\widehat{b}$ towards 0.

In sum, concerns about possible omitted variable bias caused by unobserved cloudcover conditions in other schools seems unwarranted: cloudcover across school visits is almost certainly uncorrelated and, if it was correlated, by far the most likely consequence would be attenuation of the estimated impact of cloudcover on enrolment decisions.

## 3. Conclusions

Economic models assume away any difficulty in predicting future utility for making intertemporal decisions. Abundant empirical work, however, has shown that predicting future utility is actually quite difficult and that, in particular, people tend to exaggerate the degree to which their future utility will resemble current utility, a phenomenon referred to as Projection Bias. In this article I assess whether such prediction errors are detectable in one of life most thought-about decisions, college choice.

I find that prospective students visiting the campus of a very competitive university showed a greater tendency to enrol in such university the cloudier the weather was during their visit. This is consistent with the proposition that because cloudiness makes belonging to an academically challenging institution more appealing (less aversive?) *today,* it biases upwards the estimated future utility of attending that university. Unlike previous studies of Projection Bias which focus on the impact of current utility on predicted utility, here it is most likely the impact of remembered utility that drives the effect.

The fact a decision as important as which college to enrol in can be influenced by such trivial and transparently irrelevant transient factor as cloudcover on a single day, suggests that projection bias is likely to be a rather general phenomenon, probably playing a role in an important share of intertemporal decisions. Economists interested in predicting future consumption, or in inferring consumers' future preferences based upon consumers' current decisions involving future consumption, should take into account factors that influence current utility, particularly if such factors are likely to change between the moment when a decision is made and when its consequences will be experienced.

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## References

Ariely, D. and Loewenstein, G. (2006). 'The heat of the moment: the effect of sexual arousal on sexual decision making', *Journal of Behavioral Decision Making*, vol.19, pp.87–98.

Conlin, M., O'Donoghue, T. and Vogelsang, J. (2007). 'Projection bias in catalog orders', *American Economic Review*, vol.97(4), pp.1–33.

Cunningham, M.R. (1979). 'Weather, mood, and helping behavior: quasi experiments with the sunshine samaritan'. *Journal of Personality & Social Psychology*, vol.37(11), pp.1947–56.

Dutton, D.G. and Aron, A.P. (1974). 'Some evidence for heightened sexual attraction under conditions of high anxiety', *Journal of Personality and Social Psychology*, vol.30(4), pp.510–7.

Gilbert, D.T., Gill, M.J. and Wilson, T.D. (2002). 'The future is now: temporal correction in affective forecasting', *Organizational Behavior and Human Decision Processes*, vol.88(1), pp.430–44.

Hirshleifer, D. and Shumway, T. (2003). 'Good day sunshine: stock returns and the weather', *Journal of Finance*, vol.58(3), pp.1009–32.

Loewenstein, G., O'Donoghue, T. and Rabin, M. (2003). 'Projection bias in predicting future utility', *Quarterly Journal of Economics*, vol.118(4), pp.1209-48.

Loewenstein, G. and Schkade, D. (1999) 'Wouldn't it be nice? Predicting future feelings', in (Kahneman D., Diener E. and Schwartz N. eds.), *Understanding Well Being: The Foundations of Hedonic Psychology*, pp. 85–105, New York: Russell Sage Foundation.

Rind, B. (1996). 'Effect of beliefs about weather conditions on tipping', *Journal of Applied Social Psychology*, vol.26(2), pp.137–47.

Simonsohn, U. (2007). 'Clouds make nerds look good', *Journal of Behavioral Decision Making*, vol.20, pp.143–52.