Warm Welcome: Evidence for Weather-based Projection Bias in College Choice

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Abstract

This study investigates the impact of weather during college visit dates (March-April) on yield for 975 institutions over the years 2001-2020. Weather is defined as the average temperature in each month, with indicators for unusually warm (>60°F) or unusually cold (<32°F). Additional conditions explored include yield by gender and school selectivity. Regression with institution and year fixed effects finds that unusually warm weather in April increases yield, especially for women and for students who apply to the most selective schools. A robustness condition shows that rainfall in March accounts for some negative impact on yield, but unusually warm weather in April remains statistically significant. This effect of transitory weather shocks on long term enrollment decisions may be attributable to projection bias whereby applicants misperceive short term shocks as permanent.

[1] Much thanks to my advisor Professor Jesse Rothstein for his generous support and regular guidance. Any errors remaining are my responsibility.

1. Introduction

Common advice is to not go grocery shopping while hungry. Junk food looks especially tempting to a grumbling stomach, leading to over-purchase and later regret. This phenomenon of over-projecting current mood onto a future state is known as projection bias. While its impact on grocery shopping is not overly lamentable, it can also impact more long term decisions.

One case where projection bias has been found to be important is solar investment decisions. Weather and its effect on projection bias was studied using data from the California Solar Initiative subsidy program (Liao 2020). The author found that a homeowner's decision of whether to cancel or go further with the installation of new solar panels is linked to the short-run weather conditions after sign-up. If conditions are cloudier than usual in that subsequent month, then the customer is more likely to cancel installation. Specifically, a one standard deviation decrease in solar radiation relative to normal for the location is associated with a 7-10% increase in cancellations. This is plausibly due to projection bias, as homeowners predict conditions will be similarly poor in the future even though logically there will be as many sunny days as usual to come over the long horizon relevant to the solar adoption decision.

In this paper, I focus on the effect of projection bias on the first big investment a young person makes in their life: college choice. Specifically, I ask how colder or warmer local weather than usual during admit visit months affects students' decisions to enroll in an institution in the following fall.

1.1 Literature review

On the topic of college enrollment decisions, academic rating seems like the most salient component impacting a school's popularity. There is a large literature studying how student demand depends universally on an institution's academic quality (Eccles 2010). However, new research has discovered that there are nonacademic factors that also have an influence on a student's decision to apply.

There is evidence that the consumption value of a school piques student interest. For example, Jacob et al. (2013) show that demand-side pressure by students drives school expenditures on amenities. The authors estimate student demand for school amenities using a discrete choice model. Though high-achieving students are found to have a high willingness to pay for academic quality, wealthy students would rather pay for consumption amenities, such as better dorms and sports facilities. Thus, selective schools focus spending on improving academic quality while less selective ones spend more on consumption amenities. This shows how complex student preferences are.

Out of left field comes a more obscure feature impacting student decisions studied by McEvoy (2005). The author finds that, though not reflective of a school's ability to educate, its sports teams' win rates have a significant effect on how many people apply. Data on 62 schools' performances at six NCAA Division I-A conferences between 1994-1998 were used to determine this effect. While basketball and volleyball showed no significant effects, football did have a significant association, likely due to its popularity and prominence in media. A 25 percentage point increase in winning percentage is associated with a 6.1% gain in applicants the following year, while a 25 percentage point decrease is associated with a 0.4% loss. So, there are school attributes beyond the usually considered prestige (and the associated tuition) that affect a school's attractiveness.

Combining the topics of weather and college choice is a study on the effect of cloud cover on school enrollment rates (Simonsohn 2010). It further shows that nonacademic psychological factors affect students' application decisions. The data follow 1,284 students at a university in the Northeastern US, and include information from their interviews on whether they were accepted and whether they chose to attend, as well as weather data from the NOAA coinciding with school visit dates in August-December. The author finds that a one standard deviation increase in cloud cover on campus visit days is associated with a 9% increase in enrollment probability. This was contrary to the author's initial hypothesis that sunnier weather would yield higher rates. Due to this, no clear psychological explanation for how weather affected decisions was put forward, but the author does mention that feature priming could have an effect (i.e., cloudy weather made visitors overvalue the school's academic standing to compensate).

The other side of the market is explored in another study by the same author (Simonsohn 2006). The data include 628 college admission decisions, along with ratings of the applicants on academic, social, and miscellaneous dimensions. Cloud cover data are taken from NOAA as a 1-10 cloudiness rating for each day the decisions were made. This study finds that the weather on application review dates affects a student's likelihood of being accepted. Specifically, cloudy weather increases a student's chances by 11.9%. Once again, the author theorizes that on cloudy days, academic attributes are highlighted more than non-academic ones due to feature priming (i.e., cloudy weather triggers a sad mood and more analytical way of brain processing).

I expand on Simonsohn's work on weather and student enrollment decisions through a larger-scale investigation of colleges across the country. I also look more deeply at the factors behind this relationship by discerning how effects differ by applicant gender and college selectivity, and contrast the effects of temperature and rainfall.

1.2 Overview of strategy and results

In this paper, I use data from the Integrated Postsecondary Education Data System (IPEDS) and National Oceanic and Atmospheric Administration (NOAA) databases to form a balanced panel of 975 institutions across the years 2001-2020. The panel includes institutional variables for applications, admissions, and enrollments as well as weather variables for temperature and rainfall in the months of March and April. In order to capture the college visiting months of students, I kept only the weather data for March and April. The majority of colleges send out acceptance letters in the last weeks of March, and then give students until the first of May to make their final choice. Because of this, the bulk of student visits to schools likely falls within the March-April window. I estimate panel regressions that include institution and year fixed effects to investigate the impact of the weather variables on yield (defined as the share of admitted students who enroll). The main finding is that unusually warm weather in April (>60°F) increases yield by 0.613 percentage points, or an average of 3.6%. I do not find effects of March temperatures, or of cold weather in either month. I also add specifications for yield by gender as well as school selectivity, and find that women exhibit greater reactivity to warm weather in April and that the effect of warm weather in April is unique to the most selective schools and thus the most academically competitive students. A robustness analysis adding rainfall as a possible omitted variable finds that rainfall in March is also statistically significant (it negatively predicts yield by 0.08 percentage points) but that warm weather in April remains statistically significant with its addition.

In the next section of the paper, I describe the various data sources and the process of compiling them into a single dataset. In section 3, I detail the empirical strategy and in section 4 I describe the results of the regression analysis. I end with a conclusion and discussion in section 5.

2. Data and descriptive statistics

2.1 IPEDS data and sample

IPEDS is a database with information on thousands of postsecondary institutions. The data are collected annually through surveys and contain information on a wide variety of institutional characteristics (e.g. applications, graduation rates, tuition). Every institution that participates in federal financial aid programs is required to submit these data. The survey started in 1986 and is ongoing.

The identifying directory variables I use for each institution are: institution name, identification number, state code/abbreviation, county code, and public vs. private vs. for-profit designation. The admissions module has information on applications, admissions, and enrollments which I use to determine yield. Application data apply to first-time students and are collected for institutions that do not have an open enrollment policy. The data are reported at the end of the year and refer to applicants who are enrolling in the Fall of that year. The variables I compile are: total applicants, total admissions, and total full-time enrollments. All of these variables are reported separately by gender, allowing me to test for heterogeneous effects.

In constructing the sample, I restricted the set of institutions to contain only four-year schools with over 100 students enrolled in each year. The dataset spanning the years 2001 to 2020 originally contained just over 147,000 institution-years. Once I removed the non-active schools and kept only four-year degree-granting institutions I was left with 93,100. I cleaned further by dropping schools with open-admission, under 100 students, and missing data for the variables of interest (applications, admissions, enrollment) in any year. The final IPEDS sample contains 19,760 institution-years. It is a balanced sample of 988 institutions.

Table 1 Institution summary statistics

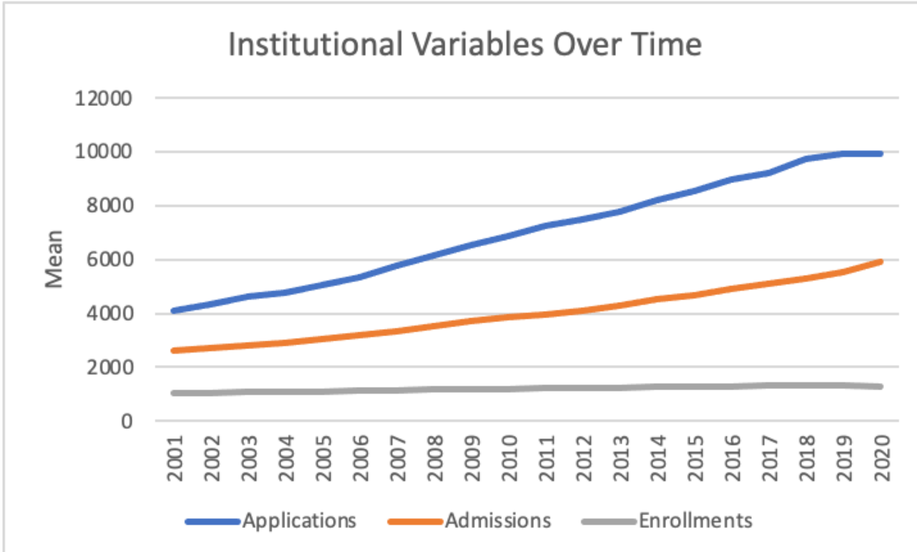
Variable	Mean	Standard Deviation
Total Applications	7,034	9,409
Male Applicants	3,123	4,368
Female Applicants	3,906	5,137
Total Admissions	4,000	4,641
Male Admissions	1,720	2,065
Female Admissions	2,279	2,636
Total Enrollments	1,201	1,351
Male Enrollments	546	641
Female Enrollments	654	729

Notes: This table shows the means and standard deviations for chosen variables from IPEDS for the balanced sample of 988 institutions. The unit of observation is institution-year (there are 20 separate observations for each school.

Table 1 shows summary statistics based on this sample. The average school in the sample has about 7,000 applications. Of these, there tends to be more from females (~55%) than males (~45%); this is consistent with current findings that women are more likely to enroll in college than men (Hussar & Bailey 2007). Based on the mean number of students admitted (4,000) and enrolled (1,201), the average selectivity of institutions in the sample is 57% and the average yield is 17%. This implies that schools admit significantly more students than end up deciding to attend. This pattern is described more deeply in the following figures.

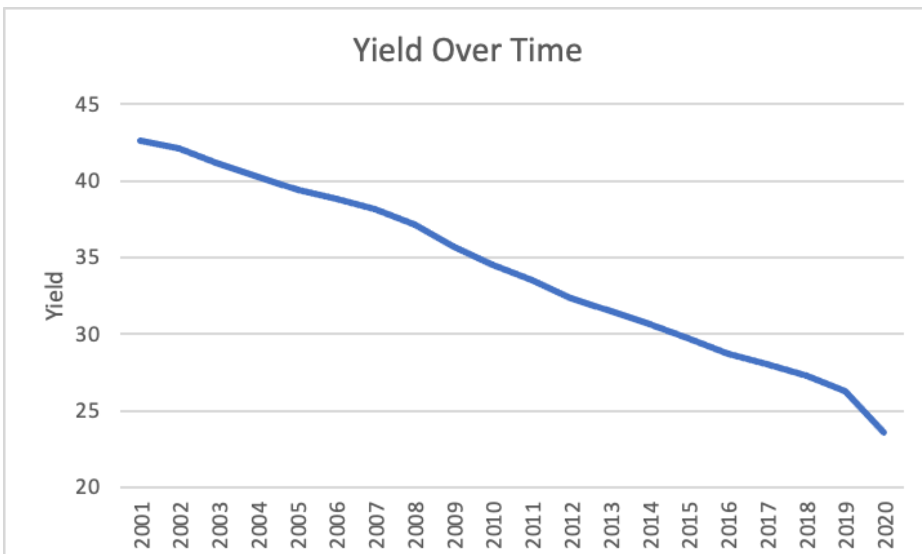
Figure 1 shows that applications and admissions to universities have both been increasing over time. However, enrollments appear pretty stable. The result of this is shown in Figure 2; increasing admissions and stable enrollments has resulted in diminishing yields over time. Average yields have fallen by more than 40%, from around 42% to less than 25%, over my study period.

Figure 1 Trends across years in applications, admissions, and enrollments



Notes: This figure shows trends in the average numbers of applications, admits, and enrollments for the sample of 988 institutions over the years 2001 to 2020.

Figure 2 Trend in average yields



*Notes: This figure shows the trend in average yield (unweighted) for the sample of 988 institutions over the years 2001 to 2020. Yield is defined as (enrollments/admissions)*100.*

One possible explanation for declining yield is that while each individual institution is receiving a greater number of applications, the number of students actually looking to enter college has not increased as dramatically. The ease of online college applications has made it possible and more popular for students to apply to a larger number of schools, including ones out of state (Dettling et al. 2018). Thus, schools that used to see only in-state applicants may be getting an increase in applications for this reason. However, each of these students can choose only one school to attend after receiving acceptances. In short, increasing applications may not mean a greater number of potential students but a greater number of applications submitted per student. Research shows that since 1940, universities have slowly turned from “a collection of local autarkies” to a “nationally integrated market,” and that this has led to greater competition between students and schools (Hoxby 1997). To compensate for this, institutions are admitting more applicants anticipating that a smaller percentage will follow through with enrollment.

2.2 NOAA data and combined sample

NOAA has past weather by county in a database called the Global Historical Climatology Network (GHCN). I downloaded the temperature (climdiv-tmpccy-v1.0.0-20211006.txt) and precipitation (climdiv-pcpncy-v1.0.0-20211006.txt) datasets from the bulk download site (https://www.ncei.noaa.gov/pub/data/cirs/climdiv/, accessed 10.27.2021). These databases contain monthly measures of temperature and rainfall from observatories across the country. The observatories number above ten thousand, with each county having at least one data collection point. The temperature measure is average monthly temperature in degrees Fahrenheit, while precipitation is reported in total inches of rainfall per month. Weather data was kept only for the months March and April to capture the visiting window for students who receive acceptances in March and must make enrollment decisions by the beginning of May.

I combined these weather data with the IPEDS sample by merging on county-year, so that the weather data are linked to the county where each institution is located. After dropping 13 schools in counties without weather data, I was left with a dataset of 19,500 institution-years with both weather and institutional data. This balanced panel represents 975 institutions present in all years from 2001 to 2020.

Table 2 shows that average temperature increases from March to April, which is consistent with expectations in the Northern Hemisphere. Average rainfall also increases from March to April, as winter changes to spring.

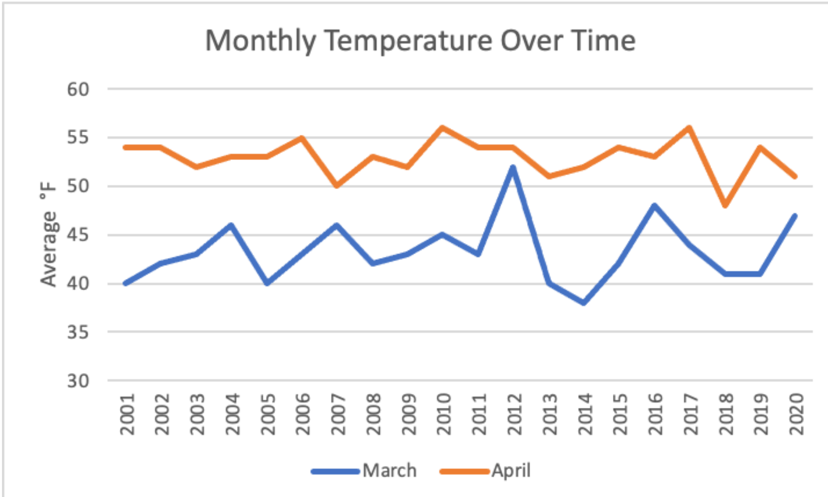
Table 2 Weather summary statistics

Variable	Mean	Standard Deviation
March Temperature	43.27	10.57
April Temperature	52.97	8.12
March Rainfall	2.79	2.19
April Rainfall	3.09	2.06

Notes: This table shows the means and standard deviations for temperature and rainfall in March and April across the 975 institutions for the years 2001-2020.

Figure 3 shows how average monthly temperature each month changed across the sample period. The average temperature for each month was calculated by averaging all observations (across all institutions and years) for that month. There is no clear trend up or down for each individual month, but April was always warmer than March.

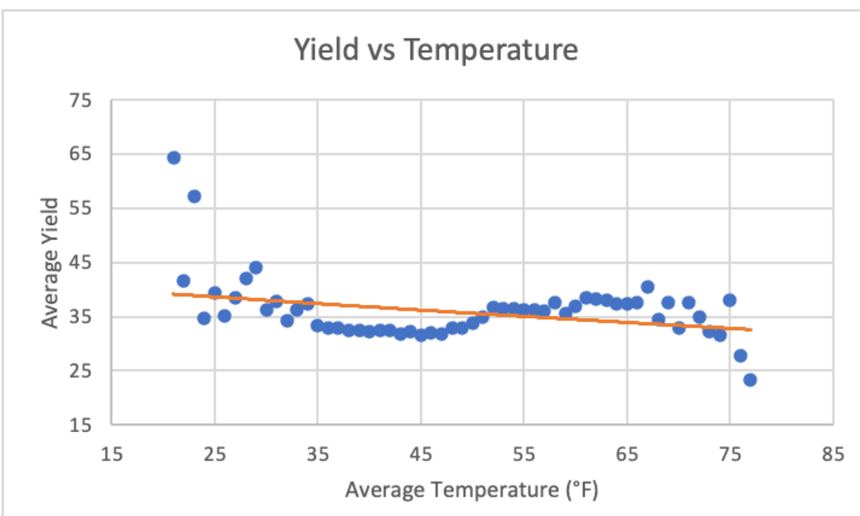
Figure 3 Trends across years in weather variables



Notes: This figure shows trends in average temperature for the two months across the 975 institutions for the years 2001-2020.

Figure 4 shows a cross-sectional relationship between average temperature across the two months and yield. The trend line is somewhat downward sloping, with the warmer data points (>70 degrees Fahrenheit) corresponding to lower yields. Interestingly, the highest yields correspond to the area where temperature is relatively cold (15-20 degrees Fahrenheit).

Figure 4 Graph of yield on y-axis vs. Average weather on x-axis



Notes: Average temperature is calculated by averaging temperature across March and April for each institution-year, and then placing these temperatures into bins (rounded to the nearest integer). Average yield is calculated for and plotted for each corresponding temperature bin.

This cross-sectional relationship could be misleading as schools of different quality can be located in areas with different weather conditions. In the next section, I describe a strategy to circumvent this and to investigate a possible causal relationship.

3. Empirical strategy

The dataset is formatted as panel data, and so I analyze it using a fixed effects regression with institution and year fixed effects.

(1) $$Y_{it} = \alpha_i + (\beta_1 * mar_{it}) + (\beta_2 * apr_{it}) + \gamma_t + \varepsilon_{it}$$

Equation 1 has yield as the dependent variable regressed on the average temperature in each month (March-April) by institution-year. Also included are institution fixed effects (α_i) and year fixed effects (γ_t). This model isolates how changes over time in weather within institutions affects changes over time in yield, getting around fixed differences across institutions in weather and yield.

The advantage of panel data and including institution fixed effects is the ability to control for fixed differences between institutions that may otherwise correlate with weather and yield. It overcomes the worry that weather may be correlated with the error term; for example, if colleges that are more desirable for other reasons tend to be in warmer areas. The fixed effects control for all potential observable and unobservable differences across institutions in their average yield and average weather. Thus, the estimated coefficients on the weather variables identify how variation in weather within institutions across years relates to the same variation in yield. For example, it answers whether yield is higher or lower than typical when April is warmer than usual. Including the year fixed effects as well accounts for possible common trends in weather and yields over time. As long as there are no unaccounted for variables that covary with weather and that also determine yield, this specification isolates causal relationships.

Since yield is defined as (enrollments/admissions)*100, a one unit increase in the weather variables corresponds to a β_1 or β_2 percentage point increase in yield.

3.1 Defining weather in two ways

The first pass of the regression defines temperature linearly as the level of the temperature variables in each month. Using the fixed effects regression, this estimates the effect of warmer or colder weather than average for a given location.

I then try an alternate definition of temperature. Since mildly warmer or colder weather is not necessarily noticeable to the average person, I next define weather in terms of hot or cold "extremes" under the hypothesis that students may be sensitive to especially warm or cold weather they experience at a school. I define unusual cold as an average monthly temperature of 32 degrees Fahrenheit or below, since that is the temperature water freezes at and thus indicates snow and more difficult conditions. To define unusually hot weather (for early spring), I select 60 degrees Fahrenheit. I originally considered 80 degrees, but with no observations at this temperature and only a couple at 70 degrees, 60 is necessary to capture more sample points (and still only represents 6.4% of the observations in March and 18.6% of the observations in April). Fixed effects are included in this regression.

3.2 Extensions: gender and institution selectivity

To expand the analysis, I consider two alternate factors that may also influence weather's impact on yield.

First, I investigate any gender differences by splitting yield into male and female subsections. I then perform the same regression with the unusual weather indicators.

Next, I consider the selectivity of each institution. Reputation and the difficulty to get into a college may overrule any negative or positive effect from weather on a student's desire to enroll. I quantify selectivity by calculating a college's acceptance rate as the number of applications divided by the number of acceptances, averaged across the sample period. I then split the sample of institutions into quartiles. Quartile 1 represents the most selective institutions, with an average acceptance rate of 40% and an average yield rate of 37%. Quartile 4 institutions are the least selective, with an average acceptance rate of 87% and an average yield of 36%.

3.3 Extension: robustness

I conclude the analysis by controlling for a possible omitted variable: rainfall. Temperature does not fully capture the weather conditions on any specific day. Adding rainfall to the regression checks the robustness of the regressions with temperature alone. I perform the previous regressions with the unusual weather indicators, gender splits, and selectivity quartiles with this additional variable added.

4. Results

4.1 Baseline results

Table 3 presents the results from estimating equation (1), which relates an institution's yield to temperatures during the college decision season. The models always include institution and year fixed effects. What differs across the two columns is how the temperature variables are defined; in column 1 it is defined as a level while in column 2 it is defined in terms of indicators for unusually cold or warm weather.

Table 3 Regressions of yield on temperature

	Continuous Temperature	Temperature Indicators
	(1)	(2)
March Temperature	-0.006 (0.02)	-
April Temperature	-0.012 (0.03)	-
March: Below 32°F	-	0.113 (0.23)
April: Below 32°F	-	-0.697 (1.49)
March: Above 60°F	-	-0.309 (0.34)
April: Above 60°F	-	0.613** (0.28)

Notes: Each column reports the results from a separate ordinary least-squares regression. The dependent variable in each case is total yield. In addition to the weather controls indicated in the row headings, institution-specific and year-specific fixed effects are included as controls. Two asterisks indicate significance at the five percent level.

The results show there is no statistically significant relationship between March and April average temperatures and yield. However, while unusually cold weather in March and April and unusually warm weather in March also have no statistically significant relationship with yield, unusually warm weather in April shows significance at the five percent level. Specifically, if April is unusually warm, yield is higher by 0.613 percentage points. Since average yield is approximately 17 percent, this translates to a 3.6% increase in yield (0.613/17). Given that this relationship only appears for one of the indicators, I focus on this “unusual weather” definition of temperature for the rest of the analysis.

4.2 Extension: heterogeneity

Next, I consider some extensions that explore whether different types of students are more or less sensitive to unusual variation in weather. The first column in Table 4 reproduces the results from the preferred specification in Table 3 for reference. Columns 2 and 3 show the results for the same specification where the dependent variable is male yield and female yield respectively. The dependent variable in columns 4-7 is again total yield, but the samples across the columns are split by institution selectivity. Selectivity falls moving across the four columns, with column 4 representing the most selective institutions and column 7 the least selective.

Table 4 Regressions of yield on temperature, by gender and institution selectivity

	All institutions			Institutions by selectivity			
	Total Yield	*Male Yield*	*Female Yield*	*Q1*	*Q2*	*Q3*	*Q4*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
March: Below 32°F	0.113 (0.23)	0.137 (0.24)	0.06 (0.24)	0.61 (0.57)	0.17 (0.35)	-0.026 (0.31)	-0.419 (0.33)
April: Below 32°F	-0.697 (1.49)	-0.979 (1.57)	-0.384 (1.55)	-1.78 (8.42)	-1.77 (1.74)	0.229 (2.06)	1.32 (2.26)
March: Above 60°F	-0.309 (0.34)	-0.33 (0.36)	-0.218 (0.36)	0.23 (0.7)	-0.43 (0.47)	-0.8 (0.57)	0.391 (0.63)
April: Above 60°F	0.613** (0.28)	0.533* (0.29)	0.671** (0.29)	1.67** (0.63)	0.15 (0.38)	-0.234 (0.42)	-0.216 (0.47)
Mean yield (%)	34	35.6	32.9	36.6	31.5	32.4	35.8
No. of institutions	975	975	975	210	219	276	270

Notes: Each column presents the results from a separate ordinary least-squares regression. All regressions include indicators for unusually hot or warm weather in March and April. In addition to the weather controls indicated in the row headings, institution-specific and year-specific fixed effects are included in the control set. Columns 1-3 include all institutions in the sample, while columns 4-7 split the institutions into subsamples based on selectivity (with quartile 1 being the most selective). One asterisk indicates significance at the ten percent level while two indicates five percent level significance.

The results of columns 2 and 3 show that unusually warm weather in April is significant for yield for both genders; it predicts a 0.53 percentage point increase in yield for men, and a 0.67 percentage point increase in yield for women. While the magnitude of these point estimates are similar, the statistical significance is only at the ten percent level for men while for women it shows significance at the five percent level. The estimated coefficient on the warm April indicator is 0.138 percentage points higher for women, suggesting women in the sample may show more projection bias as a result of weather. Though the evidence in this case is weak, the same pattern of women exhibiting greater projection bias was found in a paper on healthcare financial incentive programs (Bader 2016). The authors found that women were more likely to default on their student loan programs due to projection bias, and attributed it to women being more willing to shift future career plans to match partner preferences. This may indicate that men are more steadfast in their plans of the future and thus less likely to be affected by transitory variables such as weather.

Distinguishing by school quality shows that only the most selective schools have a significant effect of weather on yield: across columns 4-7, only column 4 shows any statistically significant estimates. Once again, this significance is seen as warmer than normal temperatures in April predicting greater yield. Specifically, if April is unusually warm, yield is higher for selective institutions by 1.67 percentage points. Since average yield at these institutions is approximately 37 percent, this translates to a 4.5% increase in yield (1.67/37). This may indicate that students who are most appealing to schools (i.e. more academically successful) are able to have more discretion in their choice of school and thus are able to take extra factors such as weather into account. This puts them more at risk of succumbing to weather-based projection bias. This may be surprising since unusual weather is not likely to repeat in the future, and the most academically accomplished students should recognize this.

4.3 Extension: robustness

I test the robustness of the model by adding total rainfall in each month as a possible omitted variable. I then run the same regressions as above (yield split by gender, institutions split by selectivity) with this new variable included.

Table 5 Robustness to adding precipitation variables

	All institutions			Institutions by selectivity			
	Total Yield	*Male Yield*	*Female Yield*	*Q1*	*Q2*	*Q3*	*Q4*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
March Rainfall	-0.08** (0.03)	-0.08** (0.03)	-0.08** (0.03)	-0.04 (0.07)	-0.03 (0.04)	-0.08* (0.05)	-0.03 (0.05)
April Rainfall	-0.05 (0.03)	-0.05 (0.03)	-0.06* (0.03)	-0.16** (0.08)	-0.03 (0.05)	-0.02 (0.05)	0.04 (0.05)
March: Below 32°F	0.11 (0.23)	0.14 (0.24)	0.07 (0.24)	0.65 (0.57)	0.17 (0.35)	-0.04 (0.31)	-0.44 (0.03)
April: Below 32°F	-0.67 (1.49)	-0.96 (1.57)	-0.37 (1.55)	-2.29 (8.42)	-1.77 (1.74)	0.26 (2.06)	1.35 (2.26)
March: Above 60°F	-0.31 (0.34)	-0.33 (0.36)	-0.23 (0.36)	0.07 (0.7)	-0.44 (0.47)	-0.78 (0.57)	0.39 (0.63)
April: Above 60°F	0.56** (0.28)	0.48* (0.29)	0.56* (0.29)	1.62** (0.63)	0.13 (0.38)	-0.26 (0.42)	-0.21 (0.47)

Notes: Each column presents the results from a separate ordinary least-squares regression. Rainfall is defined as total rainfall in inches for each month. In addition to the weather controls indicated in the row headings, institution-specific and year-specific fixed effects are included in the control set. One asterisk indicates significance at the ten percent level while two indicates five percent level significance.

The results in column 1 indicate that unusually warm temperatures in April remain significant for predicting increased yield at the five percent level when controlling for rainfall. However, the coefficient is slightly lower than when rainfall is not accounted for (0.56 versus 0.61). An additional result of note in column 1 is the significance of March rainfall on total yield; when rainfall in March is greater than normal, yield decreases by 0.08 percentage points. This result makes sense as rain is generally seen as an undesirable weather condition. This same significant negative effect of rain in March is seen even when yield is split by gender (columns 2 and 3).

The magnitude of the estimate and the significance previously seen for the warm April variable in columns 2 and 3 decrease when rainfall is added as a control variable. This indicates that some of the impact previously attributed to temperature was in fact due to rainfall.

When splitting institutions by selectivity, hot weather in April is still significant at the five percent level only for the most selective schools. Specifically, yield increases by 1.62 percentage points. Additionally, greater rainfall than usual in April is also significant at the five percent level for the most selective schools. Specifically, it negatively impacts yield by 0.16 percentage points.

High rainfall generally depresses yield in each version of the regression. However, the similarity of these results to those in Table 4 show that the original conclusion about warm Aprils is robust when rainfall is added as a possible omitted variable.

5. Discussion and conclusion

In this paper, I use annual institutional data and a fixed effects regression strategy to relate variation in weather in the months of March and April to variation in yield. The regression results show that weather during visit months does affect students' proclivity to enroll in an institution. Warmer weather in April leads to more enrollees, while greater rainfall than usual in March decreases the number who enroll. This is significant as it proves that there are additional factors besides school prestige that weigh in students' minds.

The point estimates suggest that female students may be more responsive to these differences in weather, fitting with their tendency to exhibit greater projection bias and flexibility in relation to their plans of the future (Jordyn 2018). Additionally, the significance of the weather results is concentrated in the most selective institutions, indicating that the students with the greatest competitive edge have more discretion over their school choice and are thus more likely to be influenced by weather-based projection bias in their school choice.

These results contrast with Simonsohn's findings on feature priming and enrollments: that cloudier weather leads to more applicants. This difference may be due to the fact that the study focused on a single school "known for its academic strengths and recreational weaknesses" (Simonsohn 2010). I find differences across institutions in the national sample, and this school may fall in one of the selectivity quartiles where I do not find weather influences. I also did not look at cloud cover, but at temperature and rainfall. Finally, their study focused on the months of August-December which are colder months that are timed with application decisions, while I focused on the March-April window which falls in springtime where warmer weather is more the norm and when admits are making enrollment decisions.

This work demonstrates the complexity of student enrollment decisions, and shows the impact that projection bias can have on important life decisions. Further exploration into the effect that projection bias has on our lives can help spread awareness of it and reduce the number of irrational decisions that people make on a daily basis.

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