

NBER WORKING PAPER SERIES

"FEEL" AS A DETERMINANT OF COLLEGE CHOICE:  
EVIDENCE FROM CAMPUS TOUR WEATHER

Olivia Feldman  
Joshua M. Hyman  
Matthew L. McGann

Working Paper 34944  
<http://www.nber.org/papers/w34944>

NATIONAL BUREAU OF ECONOMIC RESEARCH  
1050 Massachusetts Avenue  
Cambridge, MA 02138  
March 2026

None of the authors received any funding or have any relevant financial relationships related to this project. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2026 by Olivia Feldman, Joshua M. Hyman, and Matthew L. McGann. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

"Feel" as a Determinant of College Choice: Evidence from Campus Tour Weather  
Olivia Feldman, Joshua M. Hyman, and Matthew L. McGann  
NBER Working Paper No. 34944  
March 2026  
JEL No. I20, I23

**ABSTRACT**

The feeling or impression that students get about enrolling in a particular college may be an important determinant of their college application decision. Combining institutional records on college campus tour participants over the last decade with hourly weather information, we leverage tour weather as a plausibly exogenous shock to students' "feel" for attending the toured college. We find that poor tour weather reduces participants' likelihood of applying. Tour participants, for example, are 10 percent less likely to apply when their tour is hot and 8 percent less likely when precipitation occurs during their tour. Using administrative data documenting where all tour participants enroll in college, we find that tour weather has little to no impact on the quality or type of college that participants ultimately attend. Nevertheless, our results suggest that students' "feel" for attending a college can play an important role in the college application decision.

Olivia Feldman  
Amherst College  
ofeldman26@amherst.edu

Matthew L. McGann  
Amherst College  
mmcgann@amherst.edu

Joshua M. Hyman  
Amherst College  
Department of Economics  
and NBER  
jhyman@amherst.edu

## 1. Introduction

Most young adults in the United States enroll in some type of postsecondary education (National Center for Education Statistics, 2023). However, their choice of where to enroll has important consequences for their likelihood of completing a degree and their eventual earnings (Bound, Lovenheim, & Turner, 2010; Oreopoulos & Petronijevic, 2013; Zimmerman, 2019; Lovenheim & Smith, 2023; Mountjoy, 2026). Recent seminal papers examine determinants of students' college choices, finding, for example, that students' guidance counselors and older siblings' college choices are important determinants of where students decide to enroll (Mulhern, 2023; Altmejd et al., 2021). Another college choice determinant may be students' impression of whether they will thrive personally, academically, and socially in a particular campus environment, i.e., the “feel” that they get about attending that college. However, likely due to the challenges of measuring and finding plausibly exogenous variation in “feel,” it has been understudied in quantitative, empirical research as a possible determinant of college choice.

In this paper, we examine the importance of “feel” as a contributor to students' college choices in the context of college campus tours. Campus tours are a longstanding and ubiquitous part of the college application experience and a primary way that prospective students learn about the college environment. While tours are relatively brief and may seem like a minor aspect of the time-intensive college application process, they could play an important role in shaping students' decisions about where to apply, given students' limited opportunities to learn about the college experience. Tours are an ideal setting for researchers to learn about how “feel” affects students' college choices because colleges track whether tour participants ultimately apply to the college. No researchers, to our knowledge, have used institutional administrative data on college tours to measure the extent to which the tour experience, and subsequently a student's impression or “feel” about attending a college, can affect students' application decisions.

We leverage campus tour weather as a plausibly exogenous shock to students' “feel” for attending the toured college. Using historical administrative records from a highly-selective institution of higher education in the Northeastern U.S. containing the dates and times of campus tours linked to tour participants and hourly weather data, we examine the effect of tour temperature and weather conditions (e.g., sunny, precipitation) on participants' likelihood of applying to the institution of higher education (henceforth, “IHE”). Acknowledging that certain types of students may take tours during particular times of the day or year, that attitudes may

vary across time-of-day and season (e.g., all tour participants may be more depressed in February than in July), and that, of course, weather varies systematically across time, we use a set of temporal fixed effects to identify causal effects. Our preferred specification includes time-of-day, month-of-year, and academic term (e.g., fall 2016, summer 2023) fixed effects. We show that our results are robust to including more restrictive temporal fixed effects (e.g., month instead of academic term).

We find that poor tour weather reduces the likelihood that participants apply to the IHE. Relative to moderate temperatures, hot weather reduces applications by 2.9 percentage points (10.1%), and cold weather reduces applications by 1.7 percentage points (5.9%). Relative to sunny conditions, precipitation reduces applications by 2.4 percentage points (8.3%), and cloudy conditions reduce applications by 1.4 percentage points (4.9%). A potential threat to our analysis is that students (or their parents) who are most interested in applying to the IHE may check the weather forecast and then register to attend a tour when there is good predicted weather, creating reverse causality. We show that our results are similar, and even slightly larger in magnitude, when we restrict to participants who register online for the tour many days in advance and thus are unlikely to be choosing a date based on the predicted weather.

The negative impact of cold temperatures is driven entirely by students from warmer home states, who experience a 4.1 percentage point (14.6%) reduction. Tour weather effects tend to be larger for male than for female tour participants. For example, males are 4.0 percentage points (13.2%) less likely to apply when they experience precipitation on their tour. White tour participants experience no effects of tour weather, while Black, Hispanic, and Asian participants experience very large impacts. For example, precipitation on a tour reduces application rates by 6.2 percentage points (18.5%) among Asians.

Finally, we explore whether tour weather has meaningful longer-term impacts on participants' educational trajectories by merging all tour participants' identifying information with administrative records from the National Student Clearinghouse on whether and where participants attend college. We examine whether poor tour weather reduces the likelihood that participants ultimately enroll in any college, a four-year college, or a selective four-year college. We find no evidence that tour weather affects any of these outcomes. The likely explanation is that we do not find any discernable reduction in the likelihood of enrolling in the IHE itself. While tour weather and the subsequent "feel" that a student gets about attending a particular

college meaningfully affect the application decision, they appear to have little to no downstream impact on students' educational trajectories.

This paper, and our finding that campus tour weather impacts students' college application decisions, contributes to several economics literatures. The first is the literature examining causal determinants of college choice. In addition to studies examining effects of students' guidance counselors (Mulhern, 2023) and older siblings' college choices (Altmejd et al., 2021), other work finds that various non-academic college attributes, such as consumption amenities (e.g., dorm quality), an institution's recent athletic victories, and the share of an institution's enrollees that match the applicant's race or political identity, all influence students' application decisions (Jacob, McCall, & Stange, 2018; Pope & Pope, 2014; Black, Cortes, & Lincove, 2020; Acton, Cook, & Ugalde, 2025). An important distinction between those papers and ours is that those college attributes likely meaningfully impact students' experiences at the institution. Our paper, on the other hand, leverages a shock to a student's "feel" for attending an institution that has no bearing on the expected student experience. Due to our fixed effects identification strategy (e.g., month-of-year effects), our results are identified off of deviations from mean weather (e.g., an unseasonably hot August day), and so are not predictive of the weather a student would experience at the IHE. Thus, our identifying variation isolates "feel" itself as opposed to a preference for a particular non-academic college attribute.

In that sense, our paper is related to a small group of studies that examine mistakes in applying to college. Leveraging a policy change by ACT Inc., Pallais (2015) shows that students do not choose the optimal number and composition of institutions to which to report their ACT scores. Hoxby and Turner (2014), Larroucau et al. (2025), and Hyman (Forthcoming) all show in different contexts that prospective college students lack information and subsequently make mistakes about which colleges to apply to and attend. Our results suggest that students are letting their impression or "feel" about an institution affect their application decisions. Because our effects are identified off of deviations from typical weather, these behavioral responses and subsequent changes in college application decisions could be categorized as mistakes in applying to college.

The paper most similar to our own is Simonsohn (2010), which examines the effect of cloud cover during campus visits to an anonymous selective university by high school seniors who have already applied to the institution. The paper's main finding is that cloudy weather

*increases* the likelihood that students enroll in that institution. Simonsohn (2010) posits that worse weather (i.e., cloud cover) makes the institution more appealing, because students will spend a lot of time studying and prefer not to miss out on good weather. One possible explanation for our contrasting findings is that Simonsohn (2010) uses data from a single application year for a group of 1,284 applicants, representing the small share of applicants who visit for an optional post-application interview. Our paper’s sample is over thirty times larger, spanning eight years, and focuses on traditional campus tours attended before students apply. If the selected sample in Simonsohn (2010) are the most studious and dedicated students, then their positive reaction to cloud cover may not be representative of the average selective college applicant. Alternatively, our differing results could reflect changing applicant preferences over the last decade and a half.

Other economics of education papers evaluating the effects of weather focus on the K-12 context, examining the impacts of snowfall on learning time (Marcotte & Hemelt, 2008; Goodman, 2014) and of heat on learning (Park et al., 2020; Park, Behrer, & Goodman, 2021). Arguably more closely related to our study is the literature outside of education showing that weather influences decision-making in a manner that is difficult to reconcile with classical economic theory. For example, sunny weather on a given day increases stock market returns (Hirshleifer & Shumway, 2003), consumer spending at retail stores (Murray et al., 2010), and even convertible car sales (Busse et al., 2015). Our paper adds to this economics literature on weather and decision-making in the context of one of the most important decisions a young adult will make—where to apply to college. Our result that poor campus tour weather reduces interest in attending a college upturns the opposite finding from the closest related paper (Simonsohn, 2010) and informs college and government policy-makers that “feel” can be an effective lever to affect students’ college choices.

## 2. Background on College Campus Tours

For many decades, college campus tours have been the predominant way that potential college applicants, and their parent(s) or guardian(s) who accompany them, learn about a college’s campus and student experience. Tours are typically given by current students and involve the guide walking the participants around campus for about an hour while sharing information about the institution, academics, student life, campus dormitories, academic buildings, dining halls, and

sports and recreational facilities. Nearly all participants attend during or before the fall of their senior year, when they are considering applying to an institution, as opposed to attending during the spring of senior year after being accepted. Virtually all selective private and public four-year institutions offer tours, and most less selective four-year institutions do as well.

Campus tours at the institute of higher education (IHE) studied in this paper are implemented in a manner similar to those at most other selective colleges and universities. They are given by a current undergraduate student and offered nearly year-round, with the exception of December, January, and May when nearly all students (and therefore the tour guides) are away from campus. Tours during our sample period start on the hour from 9:00am through 3:00pm, with 9:00, 10:00, 11:00, 2:00, and 3:00 tours being more common than tours starting at 12:00 and 1:00. Tours are evenly spread across days of the week, though are less common on Sundays.<sup>1</sup> During our sample period of summer 2016 through fall 2024, tour participants registered online for a particular tour date and time. That online registration process provides us with our administrative tour participant data, described in Section 3. Tours are an hour long and are outdoors for most of the time, with the exception of brief visits inside a few campus buildings. Tour guides have designated routes they follow and required talking points, but otherwise have substantial flexibility to share and discuss whatever information and topics they wish.<sup>2</sup> At some institutions, an applicant having taken a tour is considered positively in the admissions process, but at the IHE, whether an applicant has taken a tour is not considered.

### 3. Data

Our main data are administrative records from the IHE beginning in summer 2016 through fall 2024, containing the dates and times of campus tours linked to tour participants.<sup>3</sup> The data include the date and time that each participant attends a tour, the date they apply to the IHE (if ever), and whether they enroll.<sup>4</sup> We observe participant information submitted through the online

---

<sup>1</sup> See Appendix Table 1 for the percent of our sample by time-of-day, day-of-week, and month of year.

<sup>2</sup> Our data include which student guides worked at each tour time. In a previous project version, we examined questions such as whether race-match between participant and guide affects application rates, but our analyses were underpowered due to our inability to observe which of the multiple guides working at a particular time each participant followed.

<sup>3</sup> In-person tours ceased due to the COVID-19 pandemic about halfway into the spring 2020 semester and began again in summer 2021. The data is unavailable prior to Summer 2016, when the IHE admissions office transitioned from a previous software system.

<sup>4</sup> We restrict our sample to participants who are old enough for us to observe their application decision. We observe applications through the 2024-25 academic year, i.e., for students planning to enroll during fall 2025. So, for

tour reservation form, including sex, race/ethnicity, and home address. To observe where every tour participant ultimately enrolls in college, we submit their identifying information to the National Student Clearinghouse (NSC), which contains administrative enrollment records on almost all undergraduate students nationwide (Dynarski, Hemelt, & Hyman, 2015).

We obtain detailed local historic weather data from Visual Crossing Corporation containing information about temperature, precipitation, etc.—essentially the equivalent of hourly “The Weather Channel” information—for the IHE’s zip code. Given that we do not observe household income or financial aid information for tour participants who do not apply to the IHE, we create a proxy for household income using the participant’s home zip-code level household median income from the American Community Survey during the year of the participant’s tour.

Table 1, Column 1 provides sample means of various participant and tour characteristics. Most participants are female (57.9%). The predominant racial/ethnic group is White (coincidentally, also 57.9%), with Asian the next most common (21.6%), followed by Hispanic (9.1%) and Black (4.7%).<sup>5</sup> Twenty-six percent of participants visit during the fall semester of their junior year or earlier, 32 percent visit during their spring of their junior year, and the remaining 42 percent visit as rising or fall-semester seniors. We exclude the approximately 2% of tours by spring semester seniors who are admitted and deciding whether to enroll. Our sample participants come from relatively high-income communities, with only 13.7 percent from a zip code where the average median household income is below the national median. Over half (52.7%) of participants hail from the four most popular states of New York, Massachusetts, California, and New Jersey, with the rest coming from across the country and world (5% international). The most common academic term for tours is summer (June-August; 43.9%), then spring (February-April; 35.8%), and, finally, fall (September-November; 20.3%).

As for tour weather, the distribution of temperatures (in Fahrenheit) ranges from 3 to 95.5 degrees, with 5<sup>th</sup>, 25<sup>th</sup>, median, 75<sup>th</sup>, and 95<sup>th</sup> percentiles of 33.0, 47.9, 65.0, 76.6, and 86.9 degrees as respectively. Tour conditions are most likely to be cloudy (68.0%), with smaller

---

example, we drop sophomore (and younger) tour participants during 2023-24, because they will be applying to enroll for fall 2026. We similarly drop junior year (and younger) participants during fall 2024.

<sup>5</sup> For ease of interpreting our subgroup analyses, we use mutually exclusive racial/ethnic categories, favoring the minority status, e.g., a White Hispanic student counts as Hispanic. The results are essentially identical if we instead use non-mutually exclusive categories.

shares sunny (20.8%) and with precipitation (11.1%). Participants register 20.0 days before their tour date on average, but this is skewed to the right by a small number who register many months in advance, such that the median is 13 days in advance. 28.8 percent of participants apply to the institution, and 2.2 percent ultimately enroll.

To provide a first pass at documenting the correlational relationship between tour weather and application rates, we show mean participant application rates by temperature and weather conditions (Figure 1). Figure 1a breaks tour temperatures into five groups with round-number boundaries (i.e., <40 degrees, 40-55, 55-70, 70-80, and 80+) and similar sample sizes across the groups approximating temperature quintiles. The figure reveals an inverse U-shaped relationship between tour temperature and application rates. Specifically, the application rate is just over 25% for the coldest tours, rises to nearly 32% for the middle temperature grouping, and then falls again to under 28% for hotter temperatures. Figure 1b shows that the application rate is 30% when tours are sunny, 28.7% when cloudy, and 27.5% when there is precipitation.

Figures 1a and 1b show that application rates tend to be lower when tour weather is less pleasant. However, this does not necessarily reflect the causal impact of tour weather. For one thing, students (or parents) most excited to apply to the IHE may wait for a predicted good-weather day to take the tour. As a first pass at gauging whether that concern drives the correlational relationships presented above, we restrict the sample to the 57.8% of tour participants who register at least 10 days in advance, given that participants who register far in advance are unlikely to be choosing a date based on the weather forecast.<sup>6</sup> Columns 2 and 3 in Table 1 show that the participants who registered at least 10 days in advance appear similar to those who registered less than 10 days in advance, other than having a much higher mean number of days registered in advance (32.1 compared to 3.4 days). Figures 1c and 1d, estimated using this restricted sample, show a very similar pattern of application rates by temperature and weather conditions, suggesting that participants choosing when to attend a tour based on predicted weather does not drive the correlational relationship between tour weather and application rates depicted in Figures 1a and 1b.

---

<sup>6</sup> We choose 10 days, because the 10-day mark is when forecast accuracy drops off (NOAA, 2026b). The figures look very similar when we use other nearby cut-offs, such as 7 or 13 days, and we show in Section 5 that our results are robust to using these alternative thresholds.

#### 4. Methodology

To examine the causal effect of tour weather on the likelihood of applying, we compare participants' application likelihoods across tour dates and times with different temperatures and weather conditions using a fixed effects estimation strategy. Specifically, we estimate the following ordinary least squares (OLS) regression:

$$\begin{aligned} Apply_{idt} = & \beta_0 + \beta_1 40_{dt} + \beta_2 40\_55_{dt} + \beta_3 70\_80_{dt} + \beta_4 80_{dt} + \\ & \beta_5 Cloudy_{dt} + \beta_6 Precip_{dt} + \delta_{dt} + \varepsilon_{idt} \end{aligned} \quad (1)$$

where  $Apply_{idt}$  is a binary indicator for whether student,  $i$ , who attends a tour on date,  $d$ , and at time-of-day,  $t$ , ultimately applies to the IHE,<sup>7</sup>  $40_{dt}$ ,  $40\_55_{dt}$ ,  $70\_80_{dt}$  and  $80_{dt}$  are binary variables representing whether the tours have a temperature within the respective ranges as described above and shown in Figure 1 (with range 55-70 as the omitted category),<sup>8</sup> and  $Cloudy_{dt}$  and  $Precip_{dt}$  are binary variables equal to one for tours with cloudy weather and precipitation, respectively (with sunny weather as the omitted category). We include temperatures and conditions in the same specification, so that we do not conflate the two. For example, if we separately examined temperature and conditions, we might find that the positive impact of sunny conditions masks the negative impact of hot weather (given the positive correlation between sunny conditions and hot temperatures).  $\varepsilon_{idt}$  is the error term, which we cluster at the month level.

A main threat to the validity of our causal estimates is omitted participant characteristics and other application determinants correlated with time-of-day, time-of-year, and weather. For example, different types of applicants may apply during different times of the day or year, or participant “feel” may vary systematically across times of the day or year (e.g., participants may be more tired during the morning or less enthusiastic during winter months). We add a series of temporal fixed effects,  $\delta_{dt}$ , to control for these threats. Our preferred specification includes: 1) day-of-year effects to control for omitted factors that are specific to earlier or later tours in the day and weather patterns that vary throughout the day, 2) month-of-year effects to control for

---

<sup>7</sup> Given that our main outcome variable is binary, we show that our results are virtually identical when estimated using logit.

<sup>8</sup> We show that the results are robust to different ways of creating the temperature groupings, for example, using sextiles instead of quintiles, using exact quintiles instead of approximate quintiles with round-number boundaries, and using “feels-like” temperatures that reflect wind speed and humidity.

omitted factors that are specific to different times of the year and weather varying seasonally, and finally, 3) academic-term effects (e.g., summer 2016, fall 2024) to control for possible changing weather conditions and application likelihoods over time.

Our identifying assumption is that any difference in the application likelihood across tours exposed to differing weather after conditioning on the fixed effects is due to the weather itself and not any remaining unobserved differences across tour participants. As one way to test this assumption, we show that our results are robust to including a more restrictive set of month fixed effects (e.g., August 2016, February 2023) instead of month-of-year and academic term effects.

## 5. Results

Table 2 presents the results from estimating Equation 1. In Column 1, we show the results with no fixed effects—a similar exercise to Figures 1a and 1b, except that we are examining temperature and conditions conditional on each other. In practice, this matters little, as the differences we see in Column 1 are almost identical to those shown in Figures 1a and 1b. The point estimates for the colder two groupings (i.e., <40 and 40-55) and the hottest group (i.e., 80+) are statistically significant at the 99% confidence level, while the point estimate for the 70-80 range is not statistically significant. The point estimates for the weather conditions are both significant, but only marginally for cloudy conditions.

We sequentially add in the fixed effects as we move across the columns in Table 1. Column 2 adds the academic term (e.g., summer 2016, fall 2024) effects, which attenuate most of the temperature grouping point estimates, though they remain statistically significant. Additionally, the standard errors are noticeably smaller. The coefficient on the 70-80 temperature grouping slightly increases in magnitude from -1.5 to -1.8 percentage points, and due to the smaller standard error becomes significant at the 95% level. The point estimates for weather conditions are more stable, and, as with the temperature groupings, even more precisely estimated due to the smaller standard errors. Adding the time-of-day (Column 3) and month-of-year fixed effects (Column 4) moderately changes some of the point estimate magnitudes, but the pattern is the same, and they all remain significant other than the 40-55 temperature grouping, which becomes attenuated and no longer significant.

Our preferred specification (Column 4), with the time-of-day, month-of-year, and academic term fixed effects, shows a 1.7 percentage point (5.9%) lower application rate when the tour is cold, a 2.3 point (8.0%) lower rate when the tour is warmer, and a 2.9 point (10.1%) lower rate when the tour is hot. Further, cloudy tours reduce the application rate by 1.4 percentage points (4.9%), and tours with precipitation reduce it by 2.4 points (8.3%).

It is possible that our preferred specification with academic term effects does not fully control for the threat that application rates and weather are both changing over time, even after controlling for the time-of-day and month-of-year effects. Thus, we test whether our results are sensitive to including a more restrictive set of month effects (e.g., August 2016, November 2024) rather than the month-of-year and academic term effects. We find that effects are similar to our preferred specification, with the coefficients on <40 and cloudy conditions growing slightly in magnitude, the coefficient on precipitation remaining the same, and the 70-80 and 80+ groupings attenuating slightly, all of which remain strongly statistically significant (Column 5). We also find that the point estimates remain very similar, and in fact tend to grow slightly in magnitude, when we restrict the sample to the 57.8% of participants who register at least 10 days in advance, given the previously discussed threat about enthusiastic participants possibly registering based on predicted weather (Column 6).

We conduct a number of additional specification checks that we present in Appendix Table 2. First, we use six temperature groupings (i.e., <40, 40-50, 50-60, 60-70, 70-80, and 80+) instead of using five groups. We prefer five, because there is a natural middle grouping to omit from the regression. Second, we restrict our sample to the 51% of participants who register for a tour at least thirteen days in advance, the sample median, and then to the 66% who register at least 7 days in advance. Third, we use exact temperature quintiles without round number boundaries, rather than similarly sized groupings with round-number boundaries. Fourth, we estimate the results using logit rather than OLS. Finally, we use “feels like” temperatures that incorporate wind speed and humidity. The results across all of these checks are very similar, and often almost identical, to our preferred specification. The one exception is that the cold weather result becomes somewhat attenuated, and statistically insignificant, in two of the checks, suggesting that it is somewhat less reliable than the hot temperature and weather conditions results.

Having probed the robustness of the main results, we explore heterogeneity by participant characteristics. We do not have much information about the participants, given the limited number of fields required for the online registration. We observe home address, allowing us to examine whether the effects of temperature vary by whether participants hail from a colder or hotter location. For example, a student from a hot state may be more affected by the cold, and a student from a cold state may be more affected by the heat. We show that the reduction in application rates due to cold weather is driven entirely by tour participants from hotter home states, defined as the 25 hottest states (plus DC) according to their mean temperatures over our sample period (NOAA, 2026a). Participants from hotter states are 4.1 percentage points (14.6%) less likely to apply when their tour is cold (Table 3, Column 2), while participants from colder states experience a statistically insignificant 0.3 percentage point (1.0%) reduction (Column 3).<sup>9</sup> Interestingly, the effects of hot tours are experienced equally by participants from colder versus hotter home states.

Next, we examine effects by sex and by race/ethnicity, the two participant demographics collected at the time of online registration.<sup>10</sup> While the cold temperature result is similar by sex, all of the other point estimates (hot temperatures, cloudy conditions, precipitation) are larger for males. For example, males experience a 4.8 percentage point (15.9%) reduction in application rates when their tour is hot, compared to a statistically insignificant 1.7 points (5.7%) for females. The effect of precipitation is a 4.0 point (13.2%) reduction for males, compared to a statistically insignificant 1.4 point (4.7%) reduction for females.<sup>11</sup> As for race/ethnicity, White participants comprise the largest group, yet we observe no statistically significant effects of tour weather for them. The cold temperature and weather conditions results are driven by Asian participants, while the hot temperature results are driven by Black/Hispanic students, which we pool together due to the smaller sample sizes of these groups.<sup>12</sup>

Finally, we examine whether poor tour weather affects students' ultimate college enrollment outcomes. If the IHE is one of the only colleges, one of the only four-year colleges,

---

<sup>9</sup> The p-value of the test that the coefficients on the coldest temperature grouping are equal for participants from warmer versus colder home states is 0.128.

<sup>10</sup> Note that 4.2% of participants did not submit their sex and 6.2% did not submit their race/ethnicity.

<sup>11</sup> The p-values of the test that the coefficients are equal for males and females are 0.033, 0.077, and 0.072 for the 70-80 degree grouping, 80+ degree grouping, and precipitation, respectively.

<sup>12</sup> The p-values of the test that the coefficients are equal for Whites and Blacks/Hispanics are 0.005 and 0.001 for the 70-80 degree and 80+ degree groupings, respectively. For Whites and Asians, the p-values are 0.149, 0.145, and 0.018 for the less than 40 degrees grouping, cloudy, and precipitation, respectively.

or one of the only selective four-year colleges to which a tour participant is considering applying, then not applying to the IHE could have serious implications for that participants' educational and labor market outcomes, given the returns to attending college, and especially to attending selective four-year institutions (Bound, Lovenheim & Turner, 2010; Oreopoulos & Petronijevic, 2013; Zimmerman, 2019; Lovenheim & Smith, 2023; Mountjoy, 2026). Alternatively, if tour participants apply to many institutions of similar selectivity to the IHE, or if the marginal participants induced by tour weather to not apply to the IHE would not have been admitted or chosen not to attend the IHE regardless, then there would be no impacts of tour weather on enrollment outcomes.

For simplicity, and given that we are interested in the impacts of poor tour weather, but not of specific temperature groupings or weather conditions, we create a single indicator for poor tour weather leveraging what we have learned from the previous results. This indicator variable equals one when a tour experiences any of the temperature groupings or conditions previously shown to statistically significantly reduce applications (i.e., <40 degrees, 70-80, 80+, cloudy, or precipitation). While we believe this measure provides a reasonable way to consolidate the previous results into a single indicator, 90.4% of tours fall into one of the above five weather categories. We therefore show robustness to two other poor weather proxies. The first removes cloudy conditions, given that it is the most common condition and has the smallest impact on application rates. The resulting poor weather proxy includes 61.2% of tours. Our final poor weather proxy further removes the <40-degree temperature grouping, since it has the next smallest impact, resulting in just under half of tours (49.8%) experiencing poor weather.

While all three poor tour weather proxies reduce participants' likelihood of applying to the IHE, none have a discernible impact on participants' ultimate college enrollment outcomes. Our first poor tour weather proxy reduces applications to the IHE by 2.3 percentage points (Table 4, Row 1, Column 1). However, we see near zero and statistically insignificant point estimates for effects on the likelihood of college enrollment at any college (-0.001; Column 2), a four-year college (-0.003; Column 3), and a selective college (0.002; Column 4), as defined as the highest selectivity category provided by the Barron's Profile of American Colleges (the category designated to the IHE). Our null results are fairly precise: given the standard error of 0.004 for any college, we can rule out with 95% confidence a reduction in the likelihood of

attending college of 0.9 percentage points or 1.0% off the mean enrollment rate of 86.6%.<sup>13</sup> The point estimate for enrolling in a selective institution is slightly less precise, though we can rule out with 95% confidence a reduction of 1.4 percentage points (3.1%). The reason for these null effects appears to be that there is no discernible effect on enrollment at the IHE itself. The point estimate for enrolling at the IHE is tiny in magnitude and a statistical zero (-0.003; S.E.=0.002).

The other two poor weather proxies have similar effects on application to the IHE (-2.2 and -2.5 percentage points, respectively), and on enrollment outcomes, including at the IHE, of -0.2 and -0.3 percentage points, respectively. These point estimates could be considered as precisely estimated zeros, with standard errors of 0.2 percentage points. However, it's worth noting that with application rate reductions of between 2 and 2.5 percentage points, and less than ten percent of applying participants ultimately enrolling at the IHE, we would expect an enrollment reduction of only about -0.2 percentage points, which is the exact magnitude that we observe. Thus, it is possible that poor weather is having the expected negative impacts on enrollment at the IHE, but that we do not have enough statistical power to detect it with precision. Regardless, poor weather has either a zero or a very small impact on enrollment.

Finally, we examine if poor tour weather impacts college enrollment for the subgroups of participants who we previously found to have the largest impacts of tour weather on their likelihood of applying (i.e., males and racial/ethnic minorities). Both groups, male participants and minorities, show large reductions, between 3.2 and 4.2 percentage points, in the likelihood of applying to the IHE due to poor tour weather, as proxied by all three measures (Columns 6 and 11). However, as with the overall sample, neither of these groups displays any evidence of a reduction in college enrollment outcomes.

## 6. Conclusion

The choice of where to enroll in college is a critical decision for young adults, with important consequences for their likelihood of completing a degree and their eventual earnings (Bound, Lovenheim, & Turner, 2010; Oreopoulos & Petronijevic, 2013; Zimmerman, 2019; Lovenheim & Smith, 2023; Mountjoy, 2026). It is thus important for policy-makers to understand what the determinants are of children's college choices, so that policies can be designed leveraging those

---

<sup>13</sup> We take the point estimate (-0.001) and subtract two times the standard error of 0.004, so -0.001 minus 0.008 equals -0.009, or -0.9 percentage points.

determinants to improve students' choices. Guidance counselor recommendations and older siblings' college choices have been shown to be important determinants (Mulhern, 2023; Altmejd et al., 2021), as have various non-academic college attributes (Jacob, McCall, & Stange, 2018; Pope & Pope, 2014; Black, Cortes, & Lincove, 2020; Acton, Cook, & Ugalde, 2025). Yet another likely, though understudied, determinant is simply the feeling or impression, i.e., the “feel,” that a student has about whether they will thrive at a particular college.

We use historical, administrative records from a selective institution of higher education in the northeastern U.S. (the “IHE”) on campus tour participants combined with hourly weather data to examine the impacts of tour weather on application rates. While the weather at a given time or on a given day, conditional on mean weather, has little bearing on the likely student experience at the IHE, it may impact the tour experience and the participants' subsequent “feel” for attending the IHE. We find that poor weather in the form of hot temperatures, precipitation, and even cloudiness all reduce participants' application likelihood. Male and racial/ethnic minority participants are more sensitive to poor tour weather generally, while participants hailing from hotter states are most sensitive to cold weather. These heterogeneous impacts could reflect that “feel” is a more important determinant of college application decisions for these groups. Alternatively, these groups may be more sensitive to tour weather, but may not necessarily be more sensitive to a different type of shock to students' “feel” for attending a college. Using administrative records on all participants' eventual college choices, we show that tour weather has little impact on the type or selectivity of the college in which students ultimately enroll.

Our findings are policy-relevant both for colleges and policy-makers aiming to affect students' decisions of whether and where to attend college. For colleges, knowing that “feel” matters reaffirms the importance of tours and other outreach as important in giving prospective applicants a positive impression of their institution. Admissions offices could develop tools to increase applications based on our findings, for example, nudging tour participants on the day before their scheduled tour to switch to a different time-of-day when weather is forecasted to be more favorable. For policy-makers, the federally funded College Scorecard website to help college applicants make informed decisions was motivated by the realization that applicants are underinformed about college prices, drop-out rates, and other important college characteristics. Our results motivate the development of novel interventions harnessing “feel” to improve students' college choices.

## References

- Acton, Riley, Emily Cook, and Paola Ugalde Araya (2025) “Political Views and College Choices in a Polarized America.” IZA Discussion Paper No. 18099, IZA - Institute of Labor Economics.
- Altmejd, Adam, Andrés Barrios-Fernández, Marin Drlje, Joshua Goodman, Michael Hurwitz, Dejan Kovac, Christine Mulhern, Christopher Neilson, and Jonathan Smith (2021) “O Brother, Where Start Thou? Sibling Spillovers on College and Major Choice in Four Countries.” *The Quarterly Journal of Economics*, 136(3): 1831–1886.
- Black, Sandra E., Kalena E. Cortes, and Jane Arnold Lincove (2020) “Apply Yourself: Racial and Ethnic Differences in College Application.” *Education Finance and Policy*, 15(2): 209–240.
- Bound, John, Michael Lovenheim, and Sarah Turner (2010) “Why Have College Completion Rates Declined? An Analysis of Changing Student Preparation and Collegiate Resources.” *American Economic Journal: Applied Economics*, 2(3): 129–57.
- Busse, Meghan, Devin Pope, Jaren Pope, and Jorge Silva-Risso (2015) “The Psychological Effect of Weather on Car Purchases.” *The Quarterly Journal of Economics*, 130(1): 371–414.
- Dynarski, Susan, Steven Hemelt, and Joshua Hyman (2015) “The Missing Manual: Using National Student Clearinghouse Data to Track Postsecondary Outcomes.” *Educational Evaluation and Policy Analysis*, 37(1): 53S–79S.
- Goodman, Joshua (2014) “Flaking Out: Student Absences and Snow Days as Disruptions of Instructional Time.” NBER Working Paper 20221.
- Hirshleifer, David, and Tyler Shumway (2003) “Good Day Sunshine: Stock Returns and the Weather.” *The Journal of Finance*, 58(3): 1009–1032.
- Hoxby, Caroline and Sarah Turner (2013) “Expanding College Opportunities for High-Achieving, Low Income Students.” Stanford Institute for Economic Policy Research.
- Hyman, Joshua (Forthcoming) “College Counseling in the Classroom: Randomized Evaluation of a Teacher-Based Approach to College Advising.” *Journal of Labor Economics*.
- Jacob, Brian, Brian McCall, and Kevin Stange (2018) “College as Country Club: Do Colleges Cater to Students’ Preferences for Consumption?” *Journal of Labor Economics*, 36(2): 309–348.

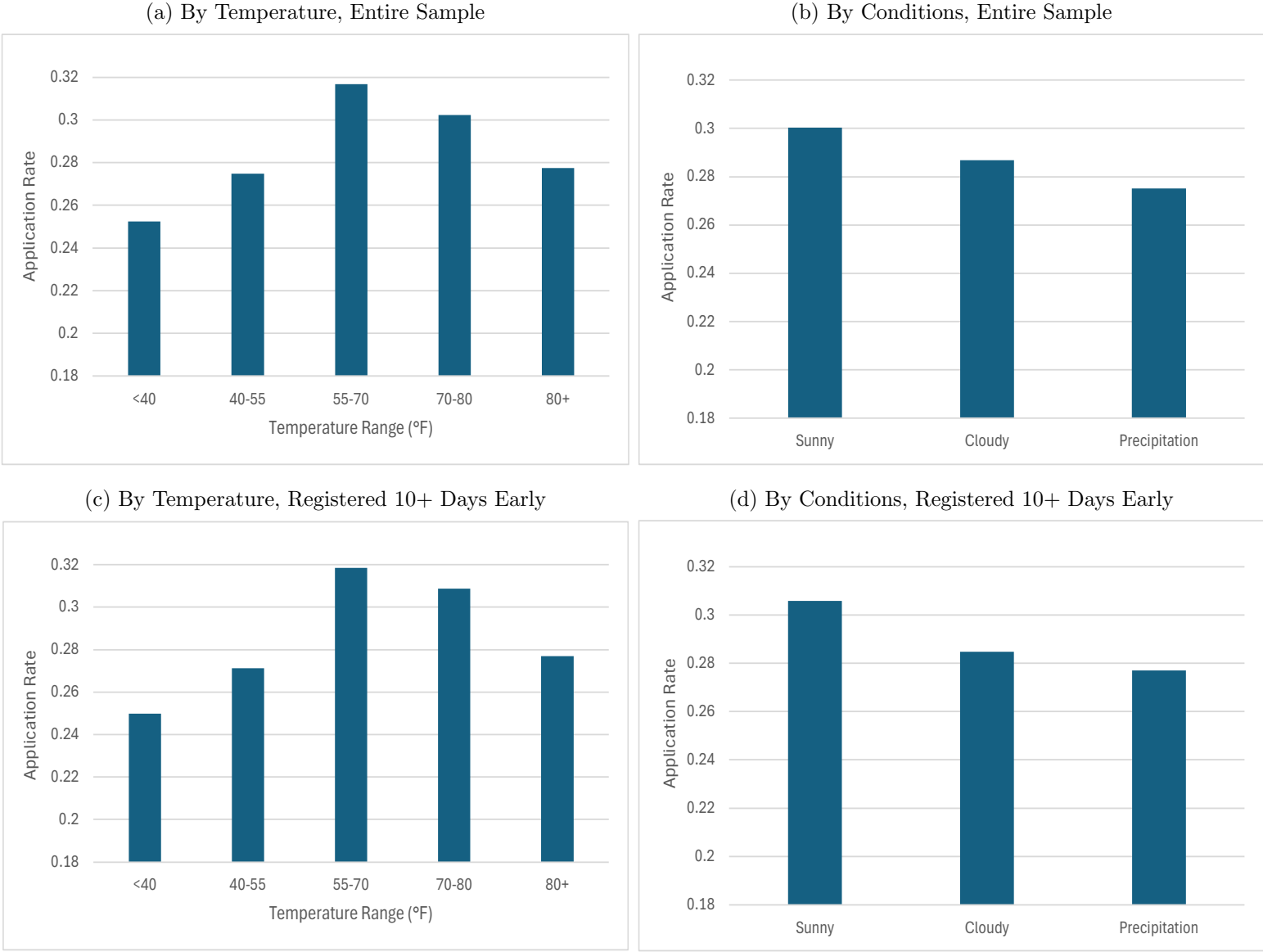
- Larroucau, Tomás, Ignacio A. Rios, Anaïs Fabre, and Christopher Nielson (2025) “College Application Mistakes and the Design of Information Policies at Scale.” Forthcoming, *Journal of Political Economy*,
- Lovenheim, Michael, and Jonathan Smith (2023) “Returns to Different Postsecondary Investments: Institution Type, Academic Programs, and Credentials.” In *Handbook of the Economics of Education*, edited by Eric A. Hanushek, Stephen Machin, and Ludger Woessmann, Vol. 6, 187–318. Amsterdam: Elsevier.
- Marcotte, Dave, and Steven Hemelt (2008) “Unscheduled School Closings and Student Performance.” *Education Finance and Policy*; 3(3): 316–338.
- Mountjoy, Jack (2026) “Marginal Returns to Public Universities.” *Quarterly Review of Economics*, 141(1): 429–497.
- Mulhern, Christine (2023) “Beyond Teachers: Estimating Individual Guidance Counselors’ Effects on Educational Attainment.” *American Economic Review*, 113(11): 2846–93.
- Murray, Kyle, Fabrizio Di Muro, Adam Finn, and Peter Leszczyc (2010) “The Effect of Weather on Consumer Spending.” *Journal of Retailing and Consumer Services*, 17(6): 512–520.
- National Center for Education Statistics (2023) “Table 302.10: Number of Recent High School Completers and Percent Enrolled in College, by Sex and Level of Institution: 1960 Through 2022,” *Digest of Education Statistics*.
- National Oceanic and Atmospheric Administration – NOAA (2026a) “Statewide Rankings.” National Centers for Environmental Information, Climate at a Glance.
- National Oceanic and Atmospheric Administration – NOAA (2026b) “How Reliable Are Weather Forecasts?” National Environmental Satellite, Data, and Information Service.
- Oreopoulos, Philip, and Uros Petronijevic (2013) “Making College Worth it: A Review of the Returns to Higher Education.” *The Future of Children*, 23(1): 41–65.
- Pallais, Amanda (2015) “Small Differences That Matter: Mistakes in Applying to College.” *Journal of Labor Economics*, 33(2): 493–520.
- Park, Jisung, A. Patrick Behrer, and Joshua Goodman (2021) “Learning is Inhibited by Heat Exposure, Both Internationally and Within the U.S.” *Nature Human Behavior*, 5: 19–27.
- Park, Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith (2020) “Heat and Learning.” *American Economic Journal: Economic Policy*, 12(2): 306–339.
- Pope, Devin G., and Jaren C. Pope (2014) “Understanding College Application Decisions: Why

College Sports Success Matters.” *Journal of Sports Economics*, 15(2): 107–131.

Simonsohn, Uri (2010) “Weather to Go to College.” *The Economic Journal*, 120(543): 270-280.

Zimmerman, Seth (2019) “Elite Colleges and Upward Mobility to Top Jobs and Top Incomes.” *American Economic Review*, 109(1): 1–47.

Figure I. Application Rates, by Tour Temperature and Weather Conditions



Notes: The sample for subfigures (a) and (b) are all 47,094 campus tour participants from summer 2016 through fall 2024. The sample for subfigures (c) and (d) are the 27,242 participants who registered online for their tour at least 10 days in advance.

Table 1. Mean Student and Tour Characteristics

	Entire	Registered in Advance	
	Sample	10+ Days	<10 Days
	(1)	(2)	(3)
Female	0.579	0.584	0.572
Race/Ethnicity			
Black	0.047	0.043	0.052
Hispanic	0.091	0.096	0.085
Asian	0.216	0.222	0.206
White	0.579	0.574	0.585
High School Grade			
Fall semester junior or earlier	0.261	0.253	0.272
Spring semester junior	0.319	0.349	0.279
Rising senior or fall semester senior	0.420	0.398	0.450
Home Zip HH Inc. Below National Median	0.137	0.135	0.141
Home State NY, MA, CA, or NJ	0.527	0.504	0.560
Academic Term			
Spring	0.358	0.388	0.317
Summer	0.439	0.420	0.464
Fall	0.203	0.192	0.218
Temperature (percentiles; °F)			
Min	3.0	3.0	9.6
5th Percentile	33.0	33.0	32.9
25th Percentile	47.9	47.1	49.3
Median	65.0	63.7	66.9
75th Percentile	76.6	76.0	77.3
95th Percentile	86.9	86.6	87.1
Max	95.5	95.5	95.5
Weather Conditions			
Sunny	0.208	0.203	0.216
Cloudy	0.680	0.683	0.677
Precipitation	0.111	0.114	0.107
Signed Up X Num. of Days Before Tour	20.0	32.1	3.4
Applied	0.288	0.288	0.288
Enrolled	0.022	0.020	0.025
Sample Size	47,094	27,242	19,852

Notes: The sample is 47,094 campus tour participants from summer 2016 through fall 2024. "Home Zip HH Inc. Below National Median" is a dummy for the student's home zip code median household income being below the national median household income. "Signed Up X Num. of Days Before Tour" shows mean number of days prior to the tour date that each participant registered online. Columns 2 and 3 are participants who registered at least 10 days and less than 10 days in advance, respectively.

Table 2. Effects of College Campus Tour Weather on Application Likelihood

	(1)	(2)	(3)	(4)	(5)	(6)
<u>Temperature (°F)</u>						
Less than 40	-0.066*** (0.014)	-0.028*** (0.008)	-0.035*** (0.009)	-0.017** (0.008)	-0.021** (0.009)	-0.029** (0.012)
40 to 55	-0.043*** (0.011)	-0.015** (0.007)	-0.018*** (0.007)	-0.006 (0.007)	-0.007 (0.007)	-0.016 (0.010)
70 to 80	-0.015 (0.011)	-0.018** (0.008)	-0.016** (0.007)	-0.023*** (0.007)	-0.021*** (0.007)	-0.020** (0.009)
80+	-0.040*** (0.013)	-0.031*** (0.009)	-0.018* (0.009)	-0.029*** (0.010)	-0.024** (0.010)	-0.028** (0.014)
<u>Conditions</u>						
Cloudy	-0.015* (0.008)	-0.014** (0.006)	-0.012** (0.006)	-0.014** (0.006)	-0.015** (0.006)	-0.023*** (0.008)
Precipitation	-0.029** (0.011)	-0.024*** (0.008)	-0.019** (0.009)	-0.024*** (0.008)	-0.024*** (0.008)	-0.029** (0.011)
Academic Term	No	Yes	Yes	Yes	No	Yes
Time-of-Day	No	No	Yes	Yes	Yes	Yes
Month-of-Year	No	No	No	Yes	No	Yes
Month	No	No	No	No	Yes	No
Sign Up 10+ Days Ahead	No	No	No	No	No	Yes
Observations	47,094	47,094	47,094	47,094	47,094	27,242

Notes: The sample is 47,094 campus tour participants from summer 2016 through fall 2024. Each column reports point estimates and standard errors from a separate regression where the dependent variable is a dummy for whether a participant applies to the institution. The mean application rate is 28.8 percent. The omitted temperature and conditions categories are 55-70 degrees (Fahrenheit) and sunny conditions, respectively. In Column 6, we restrict to participants who signed up for the tour at least 10 days in advance.

\*\*\* = significant at the 99% level, \*\* = 95% level, and \* = 90% level.

Table 3. Heterogeneous Impacts of College Campus Tour Weather on Application Likelihood

	All (1)	Home State Temp.		Gender		Race/Ethnicity		
		Hotter (2)	Colder (3)	Female (4)	Male (5)	Black/Hisp (6)	Asian (7)	White (8)
<u>Temperature (°F)</u>								
Less than 40	-0.017** (0.008)	-0.041** (0.019)	-0.003 (0.010)	-0.016 (0.011)	-0.019 (0.013)	-0.005 (0.030)	-0.045** (0.020)	-0.012 (0.010)
40 to 55	-0.006 (0.007)	-0.018 (0.014)	0.000 (0.007)	0.001 (0.008)	-0.019 (0.012)	-0.018 (0.022)	-0.019 (0.016)	-0.001 (0.008)
70 to 80	-0.023*** (0.007)	-0.031** (0.013)	-0.017 (0.011)	-0.013 (0.009)	-0.041*** (0.011)	-0.086*** (0.025)	-0.015 (0.014)	-0.011 (0.009)
80+	-0.029*** (0.010)	-0.032** (0.013)	-0.026* (0.014)	-0.017 (0.012)	-0.048*** (0.015)	-0.106*** (0.025)	-0.019 (0.020)	-0.014 (0.011)
<u>Conditions</u>								
Cloudy	-0.014** (0.006)	-0.011 (0.009)	-0.015** (0.007)	-0.012 (0.008)	-0.017** (0.008)	0.012 (0.016)	-0.033*** (0.011)	-0.012 (0.008)
Precipitation	-0.024*** (0.008)	-0.014 (0.015)	-0.028*** (0.010)	-0.014 (0.011)	-0.040*** (0.010)	-0.001 (0.020)	-0.062*** (0.017)	-0.012 (0.012)
Observations	47,094	16,929	30,165	27,252	17,853	6,490	10,153	27,257
Dep. Var. Mean	0.288	0.281	0.293	0.300	0.302	0.316	0.335	0.286

Notes: The sample is 47,094 campus tour participants from summer 2016 through fall 2024. Each column reports point estimates and standard errors from a separate regression where the dependent variable is a dummy for whether a participant applies to the institution. The omitted temperature and conditions categories are 55-70 degrees (Fahrenheit) and sunny conditions, respectively. The specification is as in column 4 from Table 2 (i.e., academic term, time-of-day, and month-of-year fixed effects). Sample sizes due not sum to 47,094 across gender and race/ethnicity subsamples due to missing demographic information. P-values from tests of equality across the subsamples reported in the main text.

\*\*\* = significant at the 99% level, \*\* = 95% level, and \* = 90% level.

Table 4. Effect of Poor Tour Weather (Defined Three Ways) on College Enrollment

	All Campus Tour Participants					Male Participants					Minority Participants				
	Applied to IHE	College Enrollment				Applied to IHE	College Enrollment				Applied to IHE	College Enrollment			
		Any	4-Year	Selective	IHE		Any	4-Year	Selective	IHE		Any	4-Year	Selective	IHE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	
Cold, Hot, Cloud, Precip.	-0.023*** (0.008)	-0.001 (0.004)	-0.003 (0.006)	0.002 (0.008)	-0.003 (0.002)	-0.042*** (0.009)	0.000 (0.007)	0.003 (0.008)	0.008 (0.011)	-0.000 (0.004)	-0.038*** (0.011)	0.007 (0.006)	0.000 (0.008)	0.006 (0.010)	0.002 (0.004)
Cold, Hot, Precipitation	-0.022*** (0.005)	-0.003 (0.004)	-0.008 (0.005)	0.003 (0.007)	-0.002 (0.002)	-0.032*** (0.008)	-0.005 (0.006)	-0.003 (0.007)	0.011 (0.009)	-0.002 (0.003)	-0.034*** (0.009)	0.003 (0.006)	-0.005 (0.007)	0.005 (0.009)	0.001 (0.003)
Hot, Precipitation	-0.025*** (0.006)	-0.001 (0.004)	-0.003 (0.006)	0.002 (0.008)	-0.003 (0.002)	-0.042*** (0.009)	0.000 (0.007)	0.003 (0.008)	0.008 (0.011)	-0.000 (0.004)	-0.038*** (0.011)	0.007 (0.006)	0.000 (0.008)	0.006 (0.010)	0.002 (0.004)
Observations	47,094	47,094	47,094	47,094	47,094	17,853	17,853	17,853	17,853	17,853	16,643	16,643	16,643	16,643	16,643
Dep. Var. Mean	0.288	0.866	0.794	0.450	0.022	0.302	0.867	0.799	0.485	0.024	0.328	0.852	0.779	0.483	0.029

Notes: The sample in Columns 1-5 is all campus tour participants from summer 2016 through fall 2024. The sample in Columns 6-10 includes only male participants, and in Columns 11-15 includes all Black, Hispanic, and Asian participants. Each cell pair reports a point estimate and standard error (in parentheses) from a separate regression where the dependent variable is the indicator variable listed in the column header and the treatment variable is an indicator variable that proxies for poor tour weather using the listed temperatures and weather conditions. For example, the treatment variable in row three equals one if the tour is in the hottest two temperature groupings or has precipitation. Selective institutions are defined as having the highest Barron's ranking (as does the IHE).

\*\*\* = significant at the 99% level, \*\* = 95% level, and \* = 90% level.

Appendix Table 1. Tour Time-of-Day, Day-of-Week, and Month-of-Year Sample Means

Time-of-Day		Day-of-Week		Month-of-Year	
9:00am	0.106	Sunday	0.063	September	0.051
10:00am	0.222	Monday	0.164	October	0.102
11:00am	0.132	Tuesday	0.150	November	0.047
12:00pm	0.088	Wednesday	0.151	December	0.004
1:00pm	0.065	Thursday	0.157	January	0.003
2:00pm	0.249	Friday	0.189	February	0.084
3:00pm	0.140	Saturday	0.125	March	0.112
				April	0.157
				May	0.002
				June	0.101
				July	0.178
				August	0.160

Notes: The sample is 47,094 campus tour participants from summer 2016 through fall 2024. This table shows the distribution of tour time-of-day, day-of-week, and month-of-year.

Appendix Table 2. Robustness Checks for Effects of Tour Weather on Application Likelihood

	Main Specification (1)	Temperature Sextiles (2)	Signed up 13+ Days (3)	Signed up 7+ Days (4)	Exact Quintiles (5)	Logit (6)	"Feels-Like" Temperature (7)
<u>Temperature (°F)</u>							
Coldest	-0.017** (0.008)	-0.019* (0.011)	-0.034*** (0.012)	-0.030** (0.012)	-0.014 (0.009)	-0.017* (0.009)	-0.006 (0.009)
Colder	-0.006 (0.007)	-0.003 (0.010)	-0.020** (0.009)	-0.015 (0.009)	-0.009 (0.008)	-0.006 (0.007)	-0.009 (0.007)
Hotter	-0.023*** (0.007)	-0.017 (0.011)	-0.025** (0.011)	-0.022** (0.008)	-0.017** (0.007)	-0.022*** (0.007)	-0.024*** (0.007)
Hottest	-0.029*** (0.010)	-0.026*** (0.008)	-0.027* (0.015)	-0.030** (0.014)	-0.019** (0.009)	-0.028*** (0.010)	-0.030*** (0.010)
Hottest (Sextiles)		-0.031*** (0.010)					
<u>Conditions</u>							
Cloudy	-0.014** (0.006)	-0.014** (0.006)	-0.026*** (0.009)	-0.019** (0.008)	-0.014** (0.006)	-0.014** (0.006)	-0.013** (0.006)
Precipitation	-0.024*** (0.008)	-0.023*** (0.008)	-0.026** (0.011)	-0.027** (0.010)	-0.023*** (0.008)	-0.024*** (0.008)	-0.024*** (0.008)
Observations	47,094	47,094	24,061	31,059	47,094	47,094	47,094

Notes: The sample is 47,094 campus tour participants from summer 2016 through fall 2024. Each column reports point estimates and standard errors from a separate regression where the dependent variable is a dummy for whether a participant applies to the institution. The mean application rate is 28.8 percent. The omitted temperature and conditions categories are 55-70 degrees (Fahrenheit) and sunny conditions, respectively. The specification is as in column 4 from Table 2 (i.e., academic term, time-of-day, and month-of-year fixed effects). In column 2, we use 6 instead of 5 temperature groupings, omitting the 4th grouping. In column 3, we restrict to those signing up at least 13 days in advance (the median). In column 4, we restrict to those signing up at least 7 days in advance. In column 5, we use exact quintiles for the temperature groupings instead of round number degree grouping boundaries. In column 6, we use logit estimation instead of linear probability models, reporting marginal effects (i.e., mean derivatives). Finally, in column 7, we use "feels-like" temperature that includes wind chill and humidity.

\*\*\* = significant at the 99% level, \*\* = significant at the 95% level, and \* = significant at the 90% level.