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ESTIMATING STUDENTS' VALUATION FOR COLLEGE EXPERIENCES

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ABSTRACT

The college experience involves much more than credit hours and degrees. Students likely derive utility from in-person instruction and on-campus social activities. Quantitative measures of the value of these individual components have been hard to come by. Leveraging the COVID-19 shock, we elicit students' intended likelihood of enrolling in higher education under different costs and possible states of the world. These states, which would have been unimaginable in the absence of the pandemic, vary in terms of class formats and restrictions to campus social life. We show how such data can be used to recover college student's willingness-to-pay (WTP) for college-related activities in the absence of COVID-19, without parametric assumptions on the underlying heterogeneity in WTP. We find that the WTP for in-person instruction (relative to a remote format) represents around 4.2% of the average annual net cost of attending university, while the WTP for on-campus social activities is 8.1% of the average annual net costs. We also find large heterogeneity in WTP, which varies systematically across socioeconomic groups. Our analysis shows that economically-disadvantaged students derive substantially lower value from university social life, but this is primarily due to time and resource constraints.

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A data appendix is available at http://www.nber.org/data-appendix/w28511

1 Introduction

Enrollment in higher education has traditionally been analyzed through the lens of human capital models, where attending college is considered an investment opportunity. However, the value students place on different aspects of the college experience likely constitutes a key factor underlying post-secondary education decisions. A growing body of evidence suggests that these valuations are not solely based on expected financial returns (Gullason, 1989; Alstadsaeter, 2011; Wiswall and Zafar, 2015; Boneva and Rauh, 2019; Arcidiacono et al., 2020). For example, Pope and Pope, 2009 show that football and basketball success increases the number of applications universities receive. Similarly, Alter and Reback, 2014 find that many institutions experience changes in applications when they suffer fluctuations in their quality-of-life reputation. These findings have also been tightly connected to colleges' investment decisions by Jacob et al., 2018, who find that universities do in fact actively cater to students' desires for non-academic experiences.

However, the precise value students allocate to the various components of their college experience is largely unknown. The aim of this study is twofold. First, we aim to rigorously recover student's willingness-to-pay (WTP) for college-related activities – specifically, the value that students assign to in-person classes (versus remote instruction) and social activities while in college. Second, we aim to characterize the heterogeneity in the WTP based on students' demographic characteristics and to uncover plausible mechanisms that can explain why some groups drop out from higher education at higher rates.

For this purpose, we leveraged variation in educational experiences generated by the COVID-19 shock, and surveyed approximately 1,500 undergraduate students at Arizona State University (ASU), one of the largest public universities in the United States, in late April 2020. ASU is a highly diverse institution and provides a sample which is broadly representative of public institutions in the US. The survey included a module to understand how students' intended enrollment decisions for the Fall 2020 semester would vary across the different possible states of the world. Specifically, students who were not planning to graduate or transfer after the spring 2020 semester were presented with six different scenarios for the fall, which varied class format (i.e., in-person vs. remote instruction), restrictions to campus social life, and prevalence of COVID-19. These scenarios were intended to mimic the possible states of the world in which students may find themselves in the fall of 2020. They were then asked for the likelihood of continuing their enrollment in each of those cases, under varying education costs (which were anchored to the student's individual annual net costs). These data allow us to estimate a simple model of expected utility of enrollment, providing a framework to recover quantitative measures of WTP. Crucially, because we elicit likelihoods for scenarios both with and without COVID-19 under control, we are able to measure students' preferences while also allowing students' outside options (the value they place on *not* attending university) to differ by the degree to which the pandemic is under control. Because our data collection conducts a kind of experiment at the individual student level, we are able to identify preferences using only within-individual variation in stated choices. This enables us to estimate individual-level preferences, providing two key advantages. First, it allows for unrestricted forms of preference heterogeneity (see Wiswall and Zafar, 2018 for related discussion). Second, it allows us to identify preferences while also permitting the impact of COVID-19 on students' outside options to differ at the individual level. Given the structure of the hypothetical scenarios, we are able to estimate the value that students assign to in-person classes and social activities while in college, in the *absence* of the pandemic.[1] We focus on these amenities in particular because they can only be consumed while a student is actively enrolled in university, and thus may capture a relevant proportion of the consumption value of a "college experience".[2] However, we acknowledge that the value of in-person instruction (relative to remote learning) and campus social activities only represent a part of the value of attending college; for example, a college degree likely offers access to higher paying jobs, even if it is obtained through remote learning.

We first show that there is substantial variation in responses, both across individuals and across scenarios. For example, the average intended likelihood of enrolling in higher education in the "normal" state of the world that mimics the pre-COVID case (in-person instruction, ongoing social activities on campus, and no COVID-19) is 89.7%. In the state of the world with no in-person instruction, no social activities on campus, and ongoing COVID-19 – the scenario that most resembles the state realized at ASU in the fall – the average intended likelihood of enrolling was 80%. The likelihood of enrolling in the COVID state is lower than the reported likelihood of enrolling in the normal state for 44.7% of the students, and identical for 45.4% of the students (the remaining 9.9% report a higher likelihood of enrolling in college in the COVID-state). The heterogeneity in responses also varies systematically by the socioeconomic and demographic characteristics of the students.

We next outline a simple model of college attendance that links student's utility to enrollment probabilities, where their utility can depend on certain amenities in school (in-person instruction and campus life), on whether the pandemic is ongoing or not, and the cost of attendance. We show how the variation in responses across scenarios, combined with variation in college costs that we experimentally manipulate within each scenario, can be used to quantify the WTP for in-person instruction and social activities in dollar terms. We start with aggregate-level estimates, pooling all the data across respondents for estimation. Our results

[1] Our framework would, in principle, also allow one to recover the WTPs for these components in the presence of COVID-19. However, because WTP in the absence of COVID-19 is the relevant measure of preferences in the medium to long-term, our survey variation focuses on identifying preferences in a world where the risks of COVID-19 are effectively mitigated.

[2] Note that in-person instruction and social activities may also provide value in the future through channels such as hiring networks or human capital production. Thus, the WTP that we estimate for these amenities may include more than just the associated consumption value. In fact, existing evidence suggests that social networks formed at university may be beneficial to students (Zimmerman, 2019). Our own analysis suggests that WTP for campus social life may, in part, reflect the economic value of stronger social ties; for example, we find that students that place a higher value on campus social life also expect to earn more at age 35.

indicate that the WTP for in-person instruction (relative to a remote format) in a world without COVID-19 represents around 4.2% of the average net cost of attending ASU (i.e., cost net of scholarships/grants), while the WTP for on-campus social activities is 8.1% of the average costs. The WTP for in-person instruction appears relatively small, which suggests that many students perceive remote classes as a reasonably good substitute for in-person classes. On the other hand, on-campus social activities appear more difficult to replace. Consistent with this, we find that students who do not think that online classes were a good substitute for in-person instruction have a significantly higher average WTP for in-person instruction.

The rich individual-level data we collect is conceptually similar to panel data where one would observe a given respondent making choices in different states of the world. This allows us to estimate the model at the individual level, and explore the heterogeneity in preferences across students. As we show, this also allows us to relax some of the identification assumptions that are implicit in the pooled estimation. The average WTP measures, that is, the individual-level WTP estimates averaged across individuals, are quite similar to those from the pooled estimation: an average WTP of 3.2% (of average annual net costs) for in-person instruction, and 7.0% for social activities. However, we find large heterogeneity in WTP across students, even after adjusting for estimation uncertainty using a standard Bayesian shrinkage procedure. For example, the 10th (90th) percentile of the individual-specific estimated WTP for in-person classes relative to remote learning is -$1,704 ($2,726) per year. This heterogeneity also varies systematically by student characteristics. For example, first-generation students' average WTP for in-person classes is only $204 per year, while second-generation students (that is, students with at least one college-educated parent) have an average WTP of $550. To provide a benchmark to these dollar amounts, the average net cost of attending ASU in our sample is $12,948 per year.[3] First-generation students also appear less willing to pay for campus social activities (on average, $547 per year versus $1,126 for second-generation).[4] Similar patterns emerge across a number of socioeconomic divides; for example, nonwhite and non-Honors students appear less willing to pay for in-person instruction and social activities, respectively.

Measured preferences may diverge across socioeconomic boundaries for a number of reasons. For example, it could be that these measures of willingness-to-pay are driven by true differences in tastes. It is also possible that perceived human capital production functions differ across socioeconomic groups, with, for example, certain groups perceiving lower returns of in-person instruction on human capital production. Conversely, it may be that differential constraints on students' time and resources generates heterogeneity, and holding these constraints constant, students actually value both the social and in-person aspects of higher education

[3] The average net cost reported by ASU for the year 2018/2019 was $14,081 (NCES College Navigator) which is very close to what we find in our sample.

[4] It is worth noting that differences in dollar amounts in WTP across demographic groups are not driven by differences in average net costs across groups, since the hypothetical costs are pinned to each respondent's own net cost of attendance.

similarly. In order to investigate the mechanisms underpinning the observed heterogeneity in the WTP, we project student-specific estimates of WTP onto a rich set of student characteristics. We find that observable characteristics are able to explain a large part of the gap in WTP for social activities for first-generation and lower-income students. One factor that explains much of the variation across socioeconomic groups is whether the student works while attending university. We find that students who work more than 20 hours per week (who tend to be disproportionately lower-income, non-Honors, and first-generation) derive substantially lower value from campus activities. This suggests that time constraints may play an important role in the utility students derive from campus social life. Even though we are unable to uncover the exact channels which drive this correlation, our analysis suggests that socioeconomic differences in students' WTP for campus social life are likely driven largely by constraints, rather than tastes.

On the other hand, the gap in lower-income students' WTP for in-person instruction remains remarkably robust to the same set of controls, suggesting that other unobservable factors explain their differential valuation for in-person instruction. We do, however, find other sensible correlates of the heterogeneity in the WTP for in-person instruction. For example, the WTP is correlated with students' previous experience with online education; those who took an average of one online class per semester pre-pandemic have, on average, a $676 lower WTP for in-person instruction. We find similarly large correlations between the WTP for in-person instruction and qualitative opinions about the online learning experience. However, none of these factors can explain the large gap by socioeconomic status (SES) in WTP for in-person instruction. Ultimately, we are unable to definitively determine if SES gaps in WTP for in-person instruction are driven by (observed and unobserved) constraints, perceptions of the human capital production function, or tastes, a policy-relevant distinction worthy of future investigation.

Like this paper, Gong et al., 2021 also provide a quantitative measure of the consumption value of college. Their approach, however, is quite different from ours and uses data on consumption during and after college and desired borrowing amounts from Berea College students. While their empirical strategy, which is based on the Euler equation for consumption, provides an overall measure of consumption value of college (relative to not enrolling in college), we provide a valuation of two specific, and well-defined, amenities consumed while attending college (in-class instruction, and on-campus social activities). Likewise, Jacob et al., 2018 estimate a model of college demand that exploits variation in attributes and enrollment within universities across cohorts. Using an approach quite different from ours (and one that entails a different set of assumptions), they find that students' demand is responsive to spending on amenities. One major advantage of our approach is that it allows us to characterize the heterogeneity in the WTP measures (a key concern for policymakers) with a unique degree of flexibility and by leveraging a unique shock. There is some work that documents systematic differences in the perceived non-pecuniary returns and valuation of a university education: Delavande et al., 2020 find that non-white British students enjoy university lectures less. Likewise, college experiences are valued differently by parental income and first-generation status of UK students (Belfield et al., 2020; Boneva and Rauh, 2019; Boneva et al., 2020). Jacob et al., 2018 also show that only high-SES and high-ability students in the US have a positive WTP for instructional spending. Our results are qualitatively in line with these findings. Further, our analysis suggests that socioeconomic differences in time/resource constraints are driving the differential WTP for campus activities.

Methodologically, our paper is related to a small but growing literature that uses strategically-designed survey questions in conjunction with structural models to understand decision-making.[5] Our approach hinges on the implicit assumption that stated choices reported in hypothetical scenarios are reflective of what respondents would do in actual scenarios. Historically, there has been concern about the plausibility of this assumption (Diamond and Hausman, 1994; Blumenschein et al., 2008; Hausman, 2012). However, growing evidence shows that the two approaches of using stated choices or actual choices yield similar estimates when the counterfactual scenarios presented to respondents are realistic and relevant (Mas and Pallais, 2017; Wiswall and Zafar, 2018). We argue that is the case here; we elicit likelihood of college enrollment in a context where many university-related activities had been disrupted due to the outbreak of COVID-19. Scenarios that would have otherwise been unfathomable prior to early 2020 (such as a state of the world with universities conducting remote teaching and halting campus activities) became realities for students. Moreover, at the time of the survey, students were actively thinking about these possibilities.[6] In fact, we show that students, when surveyed in April, perceived substantial uncertainty about the possible states of the world in Fall 2020. The scenario closest to the realized state of the nature (i.e., outbreak continues, remote classes, and restricted social activities) was assigned an average probability of 34%. In summary, our approach takes advantage of the pandemic shock to credibly uncover how students value specific college amenities.

While the assumption underlying our approach – that stated choices in counterfactual scenarios are a reasonable proxy for actual behavior in such cases – is not directly testable, we present several pieces of evidence which should further increase confidence in our empirical strategy. First, the heterogeneity in WTPs that we uncover is meaningful and systematic. For example, we find that the estimated individual-level WTP for social activities is positively correlated with the pre-COVID-19 social engagement of students, and individual-level WTP for in-person instruction is positively correlated with share of previous courses taken online, as one would expect if our approach uncovered meaningful heterogeneity in preferences. This test is similar in spirit to that conducted by Maestas et al., 2018, who show that their estimated WTPs for

[5] Examples include Delavande and Zafar, 2019 in the context of university choice, Ameriks et al., 2020 in the context of long-term care and savings, and Fuster et al., 2020 in the context of spending responses to hypothetical income shocks.

[6] At the time of the survey, students were taking remote classes and campus activities were suspended.

working conditions using hypothetical scenarios are positively correlated with the actual working conditions of the respondents. Second, we find that the students' intended likelihood of enrolling at ASU in the fall (for the state of the world that most closely resembles the one that was realized) is positively correlated with their subsequent *actual* enrollment decisions that we observe in the administrative data. In addition, we find that students who have a high WTP for both in-person instruction and social activities (i.e., those in the top tercile of the respective distributions) are 4 percentage points less likely to end up enrolling in the fall than those students with low WTPs for both characteristics (i.e., those in the lowest terciles). Controlling for standard observables, this gap increases to nearly 6 percentage points.[7] As a final piece of evidence that our assumptions are reasonable, we test out-of-sample fit by withholding two stated likelihoods for each individual, re-estimating individual level preferences, and then comparing stated differences in log-odds to predicted differences in log-odds. We see that our predicted differences are highly correlated with actual differences, suggesting that our modeling decisions and assumptions are reasonable.

Overall, we believe that our analysis has the potential to critically contribute to the important ongoing policy debate on the cost of higher education in the U.S, and provide valuable information to administrators on how to structure university fees and services in order to promote campus diversity. Our results clearly indicate that some aspects of the college experience – in-person instruction and campus life – are valued differently by students, and therefore, university attendance should not be treated as a homogeneous good. Beyond informing the policy debate, our analysis also sheds light on why certain students might enjoy the college experience less, and thus may be more likely to drop out from college. Finally, our results are also timely given that the the role of consumption value in students' educational decisions has gained renewed visibility during the pandemic.[8]

This paper is structured as follows. Section 2 describes the survey instrument and presents summary statistics. Section 3 presents the empirical framework, and discusses identification issues. Section 4 presents overall estimation results, heterogeneity in WTP, and robustness checks. Section 5 concludes.

[7]Note that what matters for Fall 2020 enrollment is the WTP for in-person instruction and social activities in a world with COVID-19. However, we only estimate these WTPs in a world without the pandemic. As long as the WTPs are positively correlated in the two states of the world, which is quite plausible, this analysis suggests that our WTP measures capture meaningful preference heterogeneity.

[8]Students from more than twenty five U.S. universities have filed lawsuits against their schools demanding partial refunds on tuition and campus fees after the closure of university campuses. They argue that the "true college experience" involves much more than credit hours and degrees, and that they are also paying for in-person interactions with professors and peers, and for the opportunity to participate in on-campus and extracurricular activities. See for example, "Students sue colleges for refunds of tuition and fees," CBS news, May 5, 2020. Also, see, for example, "IU student files lawsuit, seeks reimbursement after class moved online due to coronavirus," IndyStar, May 8, 2020.

2 Data

2.1 Survey Administration

Our data come from an original survey of undergraduate students at Arizona State University (ASU). Like other higher educational institutions in the US, the Spring 2020 semester started in person. However, in early March during spring break, the school announced that instruction would be transitioned online and students were advised not to return to campus.

The study was advertised on the My ASU website, accessible only through the student's ASU ID and password. Undergraduate students were invited to participate in an online survey about their experiences and expectations in light of the COVID-19 pandemic, for which they would be paid $10. The study was posted during the second to last week of instruction for the spring semester (April 23rd). Our sample size was constrained by the research funds to 1,500 students, and the survey was closed once the desired sample size was reached, which happened within 3 days of posting the survey.

The survey was programmed in Qualtrics. It collected data on students' demographics and family background, their current experiences (both for academic outcomes and non-academic outcomes), and their future expectations. Those data are analyzed in Aucejo et al., 2020.

Of particular interest for this study is a module in the survey, in which students were asked about the likelihood that they would enroll at ASU (or any other higher education institution) for the next academic year under different scenarios and at different tuition levels. This module was fielded to students who were not planning to graduate or transfer after the spring 2020 semester. The presented scenarios varied depending on the combination of the following factors: (1) COVID-19 ongoing or not; (2) in-person classes or not (i.e., remote learning); (3) return to campus/social life or not; and (4) COVID-19 vaccine or not. Finally, conditional on a combination of (1), (2), (3) and (4), students were asked to report the likelihood of enrolling (on a 0-100 scale) when their cost of attending ASU was changed by -30%, -20%, -10, 0%, 10%, 20%, and 30% (relative to the individual's current net costs).[9] The specific instructions were as follows: *We will next ask you the percent chance (or chances out of 100) that you will enroll at ASU in Fall 2020 in certain situations. In all these cases, assume that you cannot transfer to another college. So if you choose not to enroll at ASU, that means you will not attend any other higher educational institution either.*

The first scenario was then presented as follows: *Consider the case: The COVID-19 outbreak is CONTROLLED by Fall 2020 (and the economy RECOVERS), AND IN-PERSON classes resume in Fall 2020, AND Students CAN RETURN to campus in Fall 2020, and campus life/activities RESUME as before. What is the percent chance you will enroll at ASU in Fall 2020 (that is, you will continue your studies here at*

[9] Each student first reported their total cost of attending ASU net of scholarships.

ASU) if: the cost of an ASU education is x% higher/lower than it was for you last semester. This scenario would have corresponded to the pre-COVID state.

The second scenario, which was consistent with the state when students took the survey, was: *Consider the case: The COVID-19 outbreak CONTINUES (and the economy is STRUGGLING), AND Classes in Fall 2020 remain ONLINE/REMOTE, AND Students are told to take classes REMOTELY in Fall 2020, and campus life/activities are COMPLETELY RESTRICTED. What is the percent chance you will enroll at ASU in Fall 2020 (that is, you will continue your studies here at ASU) if: the cost of an ASU education is x% higher/lower than it was for you last semester.*[10]

In total, the survey presented students with six different scenarios combined with seven different tuition levels. Table 1 characterizes each of the different scenarios. Since the scenarios had subtle differences, two of them were followed by understanding checks to ensure that students understood what the scenario entailed. Finally, to understand the extent to which students perceived uncertainty about the future state of the world in the fall, the survey also asked: *We just asked you about what you would plan to do in different situations that could possibly arise in Fall 2020. These related to whether the Covid-19 outbreak is controlled by then, whether teaching resumes in-person, and whether campus life/activities resume in Fall 2020. We would now like to know how likely you think each of these situations are in Fall 2020. For each situation enter an answer between 0 and 100, where 0 means "absolutely no chance" and 100 means "will surely happen". Your answers to the following situations MUST sum to 100.*

Appendix B shows screenshots from the entire module.

2.2 Sample

A total of 1,564 respondents completed the survey. Ninety respondents were ineligible and dropped from the sample (such as students enrolled in graduate degree programs or diploma programs). Responses in the 1st and 99th percentile of survey duration were excluded leading to a size of 1,446. The 231 students who were planning to graduate or transfer to another institution before the start of the fall 2020 semester were ineligible for the module. 8 students with incomplete responses were dropped. Finally, to construct the main analysis sample, we dropped the 57 students who failed both of the two attention checks, resulting in a final analysis sample of 1,150 students. As we show later, our results are robust to including students who failed only one understanding check (217 of the 274 students failed only one of the two understanding checks). On average, the survey took 35 minutes to complete (median completion time was 28 minutes).

Table 2 shows how our sample compares with the broader ASU undergraduate population and the average

[10]We would like to emphasize that we separately manipulated students' price of attendance and education modality (in-person vs remote learning) and so break any perceived correlation between education costs and method of instruction.

undergraduate student at other large flagship universities (specifically, the largest public universities in each state). Relative to the ASU undergraduate population, our sample has a significantly higher proportion of first-generation students (that is, students with no parent with a college degree), and a smaller proportion of international students. The demographic composition of our sample compares reasonably well with that of students in flagship universities. Our sample is positively selected in terms of SAT/ACT scores relative to these two populations. This better performance on admission tests could be explained by the high proportion of Honors students in our sample (24% compared to 18% in the ASU population).[11] The last four columns of Table 2 show how Honors students compare with ASU students and the average college student at a top-10 university. We see that their average SAT/ACT scores are better than those of the average ASU student (which is expected) and just slightly lower than those of the average college student at a top-10 university. The share of Honors students who are white in our sample (60%) is higher than the proportion in the ASU population and much higher than the proportion of white students in the top-10 universities. Overall, we believe our sample of ASU students is a reasonable representation of students at other large public schools, while the Honors students may provide insight into the experiences of students at more elite institutions.

2.3 Descriptive Statistics

This section presents patterns in students' subjective likelihood of returning for the fall semester, with the aim to describe the variation in the data that identifies our WTP estimates. First, to characterize the degree of uncertainty that students were facing at the time of the survey, Figure 1 presents box-plots of the subjective likelihood they place on each scenario being realized. The median probabilities assigned to the scenarios vary between 3% and 30%, suggestive of students' perceiving substantial uncertainty about the situation in the fall at the time of the survey. At the same time, the box plots show that students' priors are far from uniform. The highest median probability (of 30%) is assigned to the state where the COVID-19 outbreak continues, classes continue to be remote, and social activities are restricted. This turns out to be the scenario that most resembles the state that was realized in the fall at ASU.[12] The scenario that had been the norm prior to early 2020 – where COVID-19 is under control, classes are in-person, and campus social life continues unrestricted – was assigned an average probability of 23%. Finally, the median student assigned the lowest probability to the least consistent scenario (where the outbreak is still in place and in-person instruction and social activities are reinstated), which further supports that they provided thoughtful responses. Consistent with the high level of future uncertainty, of the 1,150 respondents, only 22

[11] The Honors College at Arizona State University is a selective, residential college that recruits academically outstanding undergraduates across the nation.

[12] In Fall 2020, while ASU offered classes in a hybrid format, for all effective purposes, classes were online/remote. Likewise, campus social life was at a halt.

assigned a probability of 0 or 100 (that is, no uncertainty) to all the future states of the world. However, 58% of the respondents assigned a probability of zero to at least one scenario.

Columns (5) and (6) of Table 1 display the sample mean and median likelihoods of returning for the fall semester under the previous year's student-specific costs, respectively. Column (7) of Table 1 demonstrates that across all scenarios, many students are certain they would return (likelihood 100), but this share differs substantially across scenarios, suggesting that differences in mean likelihood are largely driven by extensive margin moves away from certainly returning. Both the average and median students report being most likely to return under the scenario most like the pre-COVID world, where classes are in-person, social life is unrestricted, and COVID-19 is controlled (Scenario 1). The average likelihoods in Scenarios 3 and 4 provide direct evidence that students value campus social life in the absence of COVID-19, as they are 2.6 percentage points less likely to return in Scenario 3, where campus social life is restricted relative to Scenario 4. Figure 2 breaks down the likelihoods in Table 1 by students' characteristics, specifically gender, lower vs. higher income (with lower-income corresponding to households making less than $80,000 per year, approximately the median income), and Honors status. In general, students report high enrollment probabilities across scenarios. However, there are important variations: for example, if we compare Panels (a) and (c) of Figure 2, all groups of students are less likely to enroll when in-person instruction and social activities are not allowed conditional on a context where the outbreak is under control. On the other hand, Panel (e) shows that students are substantially less likely to enroll if in-person instruction and social activities are in place when the outbreak is not controlled.

As we show in the next section, it is the within-individual variation that matters for identifying the parameters of interest. This is characterized in Figure 3, which presents a scatter plot of the probability of enrolling in the following two scenarios: covid-controlled/remote-instruction/social-campus-activities-*restricted* (Scenario 3) vs covid-controlled/remote-instruction/social-campus-activities-*allowed* (Scenario 4). That is, the only difference between the two scenarios is that campus social life is allowed in one case but not the other. The majority of points (87%) are weakly above the 45 degree line, indicating that students value social activities when COVID-19 is under control.

Finally, we see substantial variation in the likelihood of re-enrollment across price levels. On average, students are highly sensitive to increases in costs and almost completely unresponsive to cost reductions (see Panel (a) of Appendix Figure A1). For example, if university attendance costs would have been 20% higher (lower), the average student enrollment likelihood would decrease (increase) by 24 percentage points (0 percentage points) for the pre-COVID-19 scenario (i.e., covid-controlled/in-person-instruction/social-campus-activities-allowed). As mentioned earlier, these costs are individual-specific. Students who were paying a positive cost were asked: *"How much are you paying per semester for your education at ASU, including room* *and board? Please take into account all loans taken by you/your family (but take out any scholarships/grants that you receive that you don't need to repay)."* An analogous question was asked to those who had negative net costs of attendance. Panel (b) of Figure A1 shows the distribution of annual net costs for our sample respondents.

To conclude, in order to check the extent to which student responses are informative of their ex-post enrollment decisions, we examined whether students' intended likelihood of enrolling at ASU in the fall (for the state of the world that most closely resembles the one that was realized) correlates positively with their subsequent enrollment decisions that we observe in administrative data. This test, obviously, can only be conducted for the state of the world that was subsequently realized in the fall. Figure 4 shows that there is a positive relationship between the stated likelihood of enrolling and the share of students that actually enrolled in-person. For example, among the pool of students who reported a stated likelihood of 90% or more in the fall, the actual enrollment rate was 96%. On the other hand, among students with a stated likelihood of less than 50% of enrolling, the actual enrollment rate was 92%.

In summary, the subjective likelihood of returning for the fall semester shows important variation both within and across students, and robustness checks with actual administrative data suggest that the elicited probabilities capture meaningful information. We next outline how we can use this information to recover measures of willingness-to-pay.

3 Framework

We propose a simple model of expected utility of enrollment that provides a framework to recover quantitative measures of WTP for different college-related activities. In particular, our model intends to recover how utility of college enrollment varies under different scenarios.

Let U_{is} denote the utility that student i gets from enrolling at ASU under state/scenario s. The utility from enrollment is given by: $U_{is} = u_i(X_{is}) + \epsilon_{is}$ where $u_i(X_{is})$ denotes the preferences of individual i over the vector of characteristics X_{is} that are related to a specific scenario s (e.g., in-person classes vs remote teaching, campus activities/life vs cancellation of campus activities/life, and an individual specific price level). Finally, ϵ_{is} corresponds to the student's additional preference component for enrolling conditional on scenario s.

We specify ϵ_{is} as: $\epsilon_{is} = \delta_i + \varepsilon_{is}$ where δ_i denotes the unobserved and scenario-invariant utility level of individual i, while ε_{is} is an idiosyncratic taste shock. It is common for choice models to assume that ε_{is} is i.i.d. Type I extreme value, and independent of preferences represented by $u_i(X_{is})$.[13] Therefore, the

[13]The assumption of independence of irrelevant alternatives (IIA) is not a concern in our context because students only have

probability that individual chooses to enroll in college conditional on scenario s, is given by:

$$ProbEnr_{is} = \frac{exp(u_i(X_{is}) + \delta_i)}{1 + exp(u_i(X_{is}) + \delta_i)}. \tag{1}$$

If we assume a linear and separable utility specification, then we can parametrize the utility function as:

$$\begin{aligned} u_i(X_{is}) = \alpha_0^i + \alpha_1^i COVID_s + \alpha_2^i InPersonClass_s + \alpha_3^i CampusLife_s + \alpha_4^i (InPersonClass_s \times COVID_s) \\ + \alpha_5^i (CampusLife_s \times COVID_s) + \alpha_6^i (Vaccine_s \times COVID_s) + \alpha_7^i CostASU_{is}, \end{aligned} \tag{2}$$

where $COVID_s$ is an indicator denoting that the outbreak is not under control in state s; $InPersonClass_s$ refers to having in-person classes (instead of remote classes) in state s; $CampusLife_s$ denotes that campus social activities are allowed (instead of being restricted) in state s; $Vaccine_s$ refers to the existence of a vaccine in state s; $CostASU_{is}$ refers to student-specific university fees as specified in the scenario. Note that the preference parameters are individual-specific; given the number of observations per respondent, we are able to estimate the model at the individual level, which allows us to non-parametrically characterize the preference distribution. However, in the empirical section, we first pool the data and estimate the model under the assumption that the preference parameters are homogeneous in either the full sample or at the demographic group level.

In addition, this utility specification allows for the possibility that utility from college amenities (in-person instruction or social life) may depend on whether COVID-19 is ongoing or not. However, the variation in the data allows us to identify only some of the parameters. As we show in the next section, the main parameters of interest, α_2^i and α_3^i, are identified. These are the utility parameters for in-person instruction and social life in a world without COVID, respectively.

The dependent variable, $ProbEnr_{is}$, is the student's reported likelihood of enrolling in scenario s, elicited on a 0-100 scale (which we scale down to 0-1). Therefore, we estimate the model following the fractional response approach developed by Papke and Wooldridge, 1996, which is well suited for situations where the dependent variable takes values between 0 and 1. Moreover, it does not require manipulation of the data when probabilities of enrollment take the extreme values (0 or 1) and it is robust to censored data.[14] The parameters of the model are estimated via quasi-maximum likelihood, where the Bernoulli log-likelihood

two options (i.e., enrolled or drop-out).

[14] For example, in the empirical application used by Papke and Wooldridge, 1996, 40% of the observations are lying at the upper bound of the interval. Gallani and Krishnan, 2017 review the econometric characteristics of the fractional response model and describe its benefits relative to alternative well-established linear and non-linear econometric solutions to bounded dependent variables.

function is given by:

$$l_{is}(\alpha,\delta) = ProbEnr_{is} log\left[\frac{exp(u_i(X_{is})+\delta_i)}{1+exp(u_i(X_{is})+\delta_i)}\right] + (1-ProbEnr_{is})\left(1-log\left[\frac{exp(u_i(X_{is})+\delta_i)}{1+exp(u_i(X_{is})+\delta_i)}\right]\right). \tag{3}$$

For fractional data, the Bernoulli quasi-maximum likelihood estimator is efficient in a class of estimators containing all quasi-maximum likelihood estimators in the linear exponential family and weighted non-linear least squares estimators.[15]

Since the parameters lack direct economic interpretation, we derive the willingness-to-pay in dollars for social life without COVID as:[16]

$$WTP_{social} = -\frac{\alpha_i^3}{\alpha_i^7}.$$

And the willingness to pay for in-person instruction as:

$$WTP_{inperson} = -\frac{\alpha_i^2}{\alpha_i^7}.$$

3.1 Identification

Our scenarios vary whether there is in-person instruction vs remote teaching, campus activities/life vs cancellation of campus activities/life, whether COVID-19 is ongoing or not, and whether a vaccine for COVID-19 exists (see Table 1). The set of hypothetical scenarios presented to the students do not include all the possible combinations of options, which would have required presenting an unreasonably large number of scenarios (12 to be specific). This is not feasible since that would have increased survey length considerably, imposing a large cognitive load on respondents and reducing response reliability. In addition, certain scenarios might not have looked plausible in practice. For example, presenting students with a scenario where COVID-19 is ongoing, classes are remote, but campus social life is fully resumed is not very realistic. Therefore, we elicit students' enrollment probabilities in six different scenarios, and at seven hypothetical costs for each scenario. These allow us to identify WTP for in-person classes (relative to remote classes) and campus activities (relative to full-cancellation of campus life) in a situation where the pandemic is under control. Intuitively, differencing out the likelihood of enrolling in Scenario 1 (in Table 1) versus Scenario 4, at different cost levels, allows us to the recover the preference parameter for in-person instruction when COVID-19 is controlled (α_2). With that identified, the difference in the likelihood of enrolling in Scenario 1 versus Scenario

[15] When estimating the model, students' reported net cost of attending is winsorized below the 1st percentile and above the 99th percentile (-\$33,000 and \$80,000 respectively), in order to address the relatively small number of outlier responses.

[16] Note that taking the ratio of the marginal effects provides the same WTP values. Also note that the WTP estimates do not depend on the level of college costs. Thus, any differences in WTP estimates across individuals cannot be due to differences in costs across individuals.

3 allows us to recover the value of campus social activities when the pandemic is controlled (α_3).[17] We are also able to identify how the presence of a vaccine and having the pandemic under control itself impact students' willingness-to-pay for college enrollment. However, these are not the focus of this paper. We are unable to identify α_4^i, the parameter that governs the utility from in-person classes in a world with COVID-19. Given constraints on survey space, we did not field a scenario that would have allowed us to identify this parameter. While we can identify α_5^i, we do not focus on it in our discussion.

When eliciting the likelihood of enrolling in different states of the world, we did not instruct respondents to hold the distribution of other unspecified factors fixed. This was intentional on our part, since it is not plausible and credible to tell students that the outside option will stay the same regardless of the state of the world. The key assumption underpinning the identification of preferences is that a student's outside option - that is the value of not attending ASU - is constant across scenarios, *conditional on COVID-19*. Note that our specification provides an even larger degree of flexibility by allowing the outside options to differ across individuals through the δ_i term. In addition, the α_1^i coefficient allows the outside option for the individual to vary flexibly conditional on whether COVID-19 is ongoing or not. We argue that a constant outside option conditional on COVID-19 within individual is a reasonable assumption across scenarios where only policy decisions of ASU administrators are changing, such as between scenario 1 and scenario 4, since these decisions are unlikely to change a student's life outside of ASU. However, since outside options may differ across individuals for many reasons, we do not ascribe a strong causal interpretation to the $COVID_s$ parameter.[18]

In summary, the fact that we recovered 42 observations per student (i.e., 6 scenarios combined with 7 different tuition fees) makes it possible to identify key parameters from within individual variation. This has several advantages. First, this allows us to overcome many possible threats to identification due to omitted variable bias. Second, the rich data at the individual level allow us to the estimate the heterogeneity in preferences without making any parametric assumptions about the underlying nature of the heterogeneity.

[17] We do not have variation to identify WTP for in-person instruction and campus activities while COVID-19 is not under control. While those estimates are likely of interest in the current environment, we chose to field scenarios that would allow us to identify parameters that are of relevance more generally.

[18] It is important to emphasize that the coefficients on campus activities and in-person classes in the absence of the pandemic are not sensitive to the inclusion of other scenarios, or to the differences in outside options between a world with and without COVID-19.

4 Results

4.1 Pooled Analysis

We start with pooling the analysis, and assuming there is no heterogeneity in the preferences within group. This implicitly assumes that the change in outside options with and without the pandemic is the same across individuals (i.e., does not vary across individuals; this assumption is relaxed in the next section). While this is clearly a restrictive assumption, and one that we relax in the next section, we believe this is a natural starting point. The first row of Table 3 presents willingness-to-pay estimates for in-person classes and campus social life when COVID-19 is controlled, for the whole sample.[19] Column (1) of Table 3 displays WTP for on-campus social activities. We find that students are willing to pay $1,043 (approximately 8.1% of average annual cost) to have access to such activities.[20] Column (2) of Table 3 shows that students are willing to pay $547 more per year in order to have in-person classes (relative to remote classes); this represents 4.2% of average annual cost of attending university, and approximately half the WTP for social activities. The relatively low value students place on in-person instruction suggests that many students perceive online instruction as a close substitute. A plausible explanation for the substantially larger WTP for campus social life is a lack of direct substitutes. It is also worth noting that the value of campus social life can potentially capture things outside the direct consumption of social interaction. For example, the formation of social networks which in general are valuable for the students (Zimmerman, 2019). Section 5.3 investigates this possibility further.

These estimates may mask important heterogeneity across groups of the student population. The remaining rows of the table show the average WTP estimates for several subgroups of the student population, in order to provide an initial characterization of the heterogeneity in WTP; the model is estimated separately for each of the subgroups. We see that, for example, the WTP of second-generation students (i.e., those students with at least one college-educated parent) for in-person instruction is $926, representing 7.2% of the average cost. On the other hand, for first-generation students, the average WTP is only $133, representing 1% of the average cost (and not statistically significantly different from zero). These results are consistent with Boneva and Rauh, 2019, who find that students with college-educated parents expect to enjoy course material more than their first-generation peers. Similar patterns can be found when comparing across race and socioeconomic status (SES), which is consistent with qualitative evidence from Delavande et al., 2020, who find that non-white British university students enjoy classes and lectures less than their white peers. Similarly, Jacob et al., 2018 show that only high-SES students derive positive WTP for university spending

[19] See column 1 of Appendix Table A1 for the coefficients from which the WTP estimates in Table 3 are derived.

[20] Average cost refers to the average net cost in our sample (i.e., $12,948). For the academic year 2018/2019, ASU reported an average net cost of $14,081.

on instruction.

Turning to the heterogeneity in valuation of campus social life, we see that first-generation students assign substantially lower value to on-campus social activities than second-generation students ($436 vs $1,540). Similar patterns are observed for lower-income students versus higher-income students. Perhaps counter-intuitively, high-achieving students (i.e., Honors) seem to value social activities substantially more than their counterparts. This is likely the result of Honors students living in on-campus housing at a much higher rate (64% versus 24% for their counterparts).

A number of factors could potentially explain the relatively large gaps in preference for in-person learning and campus social life across students. Most obviously, students from different socioeconomic backgrounds may face different constraints on their time and resources. For example, students with less family resources may be more likely to supplement their income by working, and thus have less time to participate in campus activities, or live with their family and so be less likely to participate in campus events. It is also possible that students from different socioeconomic backgrounds have, or perceive themselves as having, different human capital production functions. Finally, it is possible that differences in willingness-to-pay reflect deeper differences in tastes. Appendix Table A1 displays the coefficients from the baseline pooled specification (column 1), and a separate model where the coefficients of interest are interacted with a dummy for lower-income status (column 2). The cost preference parameter for lower-income students is about 55% larger in absolute magnitude than that of their counterparts. Looking at the marginal utility for social life, the parameter is about 40% lower for lower-income students. This suggests that differences in binding resource constraints may play an important role in explaining the heterogeneity in valuation of campus social life. On the other hand, the marginal utility for in-person instruction is zero for lower-income students (with the estimate about 95% smaller than that for higher-income students), suggestive that sources of the heterogeneity in valuation for in-person instruction are somewhat different. We explore this heterogeneity further in the following sections.

4.2 Heterogeneity in WTP: A Closer Look

In order to further characterize the heterogeneity in preferences, we estimate the model separately for each individual, which allows us to non-parametrically characterize the willingness-to-pay distribution. These are our preferred set of estimates since they also relax the identification assumptions (for example, the outside option is allowed to differ across individuals in a more flexible way, and the change in the outside option conditional on the pandemic ongoing or not is also allowed to be individual-specific). Respondents without any variation in their likelihood of returning are assigned a WTP of 0, while respondents with hard-to-fit preferences (outliers which result in WTP measures below the 3rd percentile or above the 97th) are assigned the sample mean WTP.[21]

Table 4 shows several moments of the WTP distribution for the overall sample and a number of socioeconomic subgroups. Due to sampling error in the estimates, we implemented commonly used Bayesian shrinkage procedures to avoid a mischaracterization of the WTP distribution (Appendix Table A2 presents the unadjusted moments, which are qualitatively similar). The first row shows moments of the WTP distribution for the full sample: the average WTP for social life and in-person instruction are \$906 and \$419. These translate into 7.0% and 3.2% of the average annual cost of attending university, quite comparable to the estimates in Table 3 for the pooled estimation (though there is no reason why the two approaches should give similar results, since the identification assumptions are different). The median student assigns little value to social life or in-person instruction. However, there is substantial heterogeneity: at least 10% of the students are willing to pay more than \$3,000 (\$2,700) for social life (in-person instruction) per year. Figure 5 plots the cumulative density function (CDF) of WTP for in-person classes and campus-related social activities for the entire sample.[22] These CDFs highlight the fact that more than 40% of respondents assign a positive value to each of the factors in question. Approximately 20% of respondents had a negative WTP for campus social life, while the distribution of WTP for in-person instruction appears more symmetric around zero (with 33% of students assigning a negative WTP for in-person instruction).[23]

The subsequent rows of Table 4 show that even within subgroup there is substantial heterogeneity, with the difference between the 10th and 90th percentiles of the individual-specific WTPs being more than \$3,000 for almost every demographic group. The 90th percentiles are sizable: second-generation and higher-income students at this percentile are willing to pay nearly \$3,500 for each of the two amenities (social life and in-person instruction). First-generation and lower-income students at the 90th percentile are willing to pay approximately \$2,000 for these amenities. There is even a meaningful share of students with negative willingness-to-pay for both in-person and on-campus social activities, leaving the median across most groups around \$0.

It is important to highlight that a large share of students assign a WTP close to zero for both campus amenities (relative to the baseline option), where 27 (22) percent of students assign a WTP of between \$10 and -\$10 to social life (in-person instruction). This suggests that, for some students, the intended likelihood of enrolling in higher education is not sensitive at all to the provision of these amenities. This should not be

[21]Results remain similar if instead these individuals are assigned a WTP of zero.

[22]The plots in Figure 5 display distributions for WTP adjusted for Bayesian shrinkage. This adjustment moves estimates with more uncertainty (higher standard error) closer to the sample mean, which explains the jump in the CDFs precisely at the sample mean.

[23]While ASU provides a large number of online classes, most undergraduate courses are not available online, and therefore students are forced to take them in-person.

surprising: there are other motivations for enrolling in higher education (e.g. financial incentives), and so we may assume that some students will always enroll, regardless of the consumption value provided by the institution. Interestingly, the correlation between the WTP for the two factors is negative, -0.078 (p-value = 0.008). This can be seen in Appendix Figure A2, which shows a scatterplot of the individual-specific WTPs for the amenities.

Finally, the top row of Figure 6 shows that there is substantial heterogeneity in the WTP within demographic groups. For example, panel (a) shows that the cumulative density distribution of the WTP for campus social life differs systematically by students' socioeconomic background (parents' income). Confirming this visual evidence, a Kolmogorov-Smirnov test rejects the equality of distributions with a p-value less than 0.01. However, even within these subsamples, there is substantial heterogeneity. For example, 27 (15) percent of higher-income (lower-income) students assign a WTP of more than \$1,000 for campus social life. Panel (b) shows qualitatively similar patterns for the WTP for in-person instruction. However, between-group differences are smaller in this case: we see that 22 (16) percent of higher-income (lower-income) students are willing to pay more than \$1,000 for in-person instruction.

In summary, the evidence shows large heterogeneity in WTP for key amenities of the college experience, suggesting that some of the most ubiquitous aspects of higher education (i.e., in-person classes and campus social activities) are not necessarily valued equally for a large share of students. Further, an important share of students appear to place very little value on these amenities. In the next section, we explore why this could be the case.

4.3 Heterogeneity in WTP: Mechanisms

In order to evaluate plausible mechanisms behind the large heterogeneity in willingness-to-pay for in-person classes and on-campus social activities, we project our individual estimates of WTP on three broad groups of covariates: demographics (i.e., gender, socioeconomic background, race, first generation, honors, and grade level), economic-related factors (i.e., working while attending university, working a high number of hours, total (gross) education expenditure per year, loans, scholarships, and costs above in-state fees), and non-economic factors (i.e., attendance of social events per week pre-COVID, study hours per week, ACT scores, and whether the student took on average at least one online/hybrid class per semester since enrolling at ASU). While these regressions cannot necessarily be given a causal interpretation, we believe they are still informative about the possible mediating factors that drive the heterogeneity in our WTP estimates.

Appendix Table A3 provides summary statistics for the economic and non-economic factors, conditional on the various demographic groups. In many cases, the differences across groups are sizable. For example, lower-income and first-generation students are significantly more likely to work more than 20 hours per week relative to their counterparts. Further, we see that higher-income, Honors, and freshman students are significantly more likely to partake in social activities pre-COVID.

The first three columns of Table 5 show OLS coefficients from regressions of individual estimates of WTP for on-campus social activities onto these three broad groups of covariates. Dummies for the 12 ASU colleges a student's major belongs to are also included, but do not show interesting heterogeneity in WTP.[24] Column (1) serves as a benchmark showing the level of heterogeneity in WTP across demographic groups. Lower-income and first-generation students tend to derive lower value from social activities, while the opposite is true for academically younger students. Column (2) shows that an important predictor of WTP for on-campus social activities is working more than 20 hours per week while attending college. The estimate indicates that students who work high hours during college are willing to pay $524 less per year for campus social life compared to their peers. We also find that students' total gross expenditure on education (including parental contributions, grants, and scholarships) is positively associated with the WTP for campus social life, and that students with loans show a lower WTP. As the fixed cost of attendance (including scholarships and grants) is constant across students, conditional on in-state status, differences in gross education expenditure are likely derived from consumption on things such as room and board, food, and activities. Then, the positive coefficient on expenditure indicates that campus social life complements the other types of goods students consume as education expenditure. Many potential channels could explain this complementary. For example, it could be that more consumption increases opportunities to build social networks which in turn improve post-education labor market outcomes, or it could be that some aspects of campus social life require additional expenditure to enjoy, and so are only available to students with sufficiently high education expenditures.

Together, the economic covariates explain more than 40% of the gap in WTP that we observed for first-generation students and more than 45% of the gap for lower-income students. This suggests that time and resource constraints may be an important factor in understanding why lower-income and first-generation students derive lower value from such activities. Appendix Table A1 supports this conjecture by demonstrating that differences in WTP of campus social like across income groups is driven more by differences in the expected value of education costs, rather than differences in expected value of campus social life. Finally, column (3) adds the non-economic covariates, which further help to explain heterogeneity across demographic groups. The change in the R-squared across the three columns is also informative. The demographic variables in column (1) explain little of the cross-sectional variation in the estimated WTPs;

[24]The colleges are: Business, Design and the Arts, Engineering, Health Solutions, Integrative Sciences and Arts, Journalism, Liberal Arts and Sciences, New College, Nursing and Health Innovation, Public Service and Community Solution, Sustainability, Teachers College.

this underscores the fact that there is substantial heterogeneity within demographic groups. However, the inclusion of economic factors in column (2) more than doubles the R-squared. The non-economic factors do seem to matter as well, but lead to a smaller increase in the R-squared. The results in column (3) also support the conclusion that our estimates of WTP are in fact capturing meaningful heterogeneity. In particular, we find that students who attended more social events per week prior to COVID-19 derive higher WTP for social activities. Additionally, we find that students who lived on campus pre-COVID, and thus may be more likely to participate in on-campus social activities, had a much higher WTP for campus social life.

As previously mentioned, the value of campus social life may, in part, be due to the formation of social networks which provide advantages on the job market or insulate members from bad shocks. We find evidence of this in our survey; students with higher social WTP expect to make more money at age 35, with a $1 per year increase in WTP associated with an average increase of $0.81 in expected annual earnings.

Returning to Table 5, the last three columns repeat a similar analysis but for the WTP for in-person classes. Column (4) shows that Honors students show the largest average willingness-to-pay for in-person classes (though estimates are not precise), while lower-income show the lowest WTP. Overall, our covariates seem to show a lower explanatory power for in-person WTP. For example, column (4) shows that the mean WTP for lower-income students is $535 lower relative to high-income counterparts. This hardly changes once we include the economic and non-economic factors in the next two columns. We also see that the R-squared changes much less across columns (4) to (6). However somewhat reassuringly, we do find that students who had taken more online/hybrid classes pre-COVID show a statistically significant lower WTP for in-person classes. This correlation reinforces our claim that for many students remote classes do constitute a good substitute for in-person classes. Finally, panels (c) and (d) of Figure 6 display the cumulative density distribution of WTP measures conditional on the covariates in Table 5, and demonstrate that the explanatory power of the covariates is primarily in the $0-$1,000 range of WTP. In fact, we see that the residualized WTP distributions are no longer statistically different between groups.

Digging into the in-person WTP estimates further, we find additional meaningful correlations, which suggest the lack of explanatory power in columns (4) to (6) in Table 5 is not because of noisy estimates, but rather a lack of meaningful correlation with the covariates in question. First, students who rated the learning experiences during Spring 2020 in online/remote classes as slightly, moderately, or much worse than in-person classes (76% of the sample) were willing to pay $798 more for in-person classes.[25] Students who rated the online learning experience as worse than in-person were further asked if this was because they

[25] The specific question wording was *"How would you rate your learning experiences in the online/remote classes relative to in-person classes? Please answer on a 1-7 scale."* 76% of the students chose 5, 6, or 7.

often had computer or internet problems. We do not find evidence that students with technology issues have lower willingness-to-pay for in-person instruction conditional on their opinion of learning experiences.

Students were also asked their expected semester GPA in a world with and without COVID-19. We find that WTP for in-person instruction is strongly correlated with expected changes in semester GPA due to COVID, with a 1 letter-grade (1 point) decrease in expected semester GPA associated with a $649 higher WTP for in-person instruction. However, again we find that this correlation cannot explain the socioeconomic status gap in WTP for in-person instruction.

The strong correlations between WTP measures for in-person instruction and both respondents' opinions of online learning and their experience with the switch to online learning mid-semester strongly suggest that our WTP measures are not too imprecise to pick up meaningful correlations with covariates such as employment or expenditure in Table 5. Together, these results lead to a somewhat unsatisfying conclusion, that some factors besides those in Table 5 must explain the striking heterogeneity for in-person instruction by socioeconomic status. We are ultimately unable to determine if these factors are other constraints, perceived differences in future value of these experiences through channels such as networks or human capital production, or if they are truly due to differences in tastes for mode of instruction. However, it is reassuring that heterogeneity in WTP for instruction based on socioeconomic status constitutes an empirical regularity that has also been described in the other studies (Delavande et al., 2020; Boneva and Rauh, 2019; Jacob et al., 2018).

4.4 Robustness Checks

We conclude the empirical analysis with a series of robustness checks.

4.4.1 Dropping Unlikely Scenarios

One concern with the estimates in Table 3 is that responses may be biased in cases where students did not perceive a scenario as very likely. The idea being that students may not have answered meaningfully to scenarios they expect to be implausible. To address this, we re-estimate the model by restricting the sample to only scenarios in which a student placed a positive likelihood of realization. This drops 9,751 observations out of 48,300 (observations here being at the individual x scenario x cost level). These estimates are shown in the second column of Table 6. We see that our estimates are qualitatively quite similar to those in the main sample (which are presented in the first column of Table 6). This suggests that our estimates are robust.

4.4.2 Insufficient Student Effort

Another concern with any survey data is that respondents may not take the survey seriously, and that there might be substantial measurement error in responses. While non-classical measurement error should not systematically bias our responses, one might still worry about the extent of measurement error in our estimates.

While we do not directly observe student effort, we have proxies of student attention. As mentioned earlier, the module included two understanding checks. Our main estimation sample only excludes respondents who answered both checks incorrectly. Here, as a robustness check, we also exclude the 217 respondents who answered either question incorrectly. Estimates are presented in the third column in Table 6. We see that the quantitative and qualitative estimates are very similar those in our main estimation sample. This suggests that low student effort on the survey is unlikely to explain our results. If it were the case that low survey attention was correlated with strongly biased responses and this correlation explained our results, we would have expected the estimates to change.

Further, as an additional check, we remove students from the analysis who either spent too little time or too much time on the survey pages which presented the scenarios. Specifically, we remove students whose time on those pages was in the bottom and top 5 percentiles of the cross-sectional distribution (this removes students who spent less than 16 minutes or more than 88 minutes). Estimates based on this restricted sample are presented in the fourth column of the table. Again, we see that our estimates are robust to this check.

4.4.3 Model Validation

Is the model of expected utility presented in section 3 a good representation of individuals' choice behavior? To investigate this question, we conducted a validation exercise in which two observations are withheld per individual, preferences are re-estimated within the restricted dataset, and predicted change in log odds within the withheld observations is compared to the stated change. Withheld observations were selected at random by drawing a price level and two scenarios (without replacement) independently for all respondents. The assumption of type 1 extreme value errors results in a linear in log-odds model, such that the difference in log-odds of returning to ASU between two scenarios is equal to the difference in coefficients across the two scenarios.

Figure 7 panel (a) displays the actual differences in log-odds against the predicted difference in log-odds for the observations which had interior stated likelihoods (and so, for which log-odds can be constructed) for both the excluded observations. A well specified and precise model should have estimates near the red 45-degree line. By this measure, our model does remarkably well in predicting out-of-sample decisions, suggesting that our modeling assumptions are reasonable. Further, the good out-of-sample fit in Figure 7 panel (a) provides another piece of evidence that students' stated likelihoods are meaningful, as random responses would not have predictive power over out-of-sample decisions.

Extending the validation exercise further, Figure 7 panel (b) visualizes the advantage in out-of-sample fit of the individual-level preferences compared to pooled estimates. Specifically, it plots the distribution of the model error in log-odds differences using the two approaches. We see that the individual model produces more precise estimates: the model error distribution is more concentrated around zero and has a smaller standard deviation.

Finally, if our procedure uncovers meaningful WTP estimates, they should be systematically correlated with actual enrollment behavior. More specifically, in that case, we should see that students who have a low WTP for both social life and in-person instruction (both amenities that were effectively not provided in Fall 2020 at ASU) should be more likely to have enrolled in Fall 2020, relative to students who have high WTPs for both amenities. It should, however, be cautioned that we only estimate the WTPs for these amenities in the absence of COVID-19. What really matters for the actual enrollment decision is the WTP for these amenities in the presence of COVID-19, which our setup does not allow us to identify and estimate. However, as long as the WTPs are positively correlated in both states of the world, this test should be meaningful. This is exactly what we find: 94.9% of the students with WTPs in the lowest terciles of the respective distributions enroll in the fall versus 90.4% of students with WTPs in the highest terciles (the difference is, however, not statistically significant at conventional levels, p-value = 0.209). However, since WTP estimates systematically differ by demographic characteristics (Table 5), a concern could be that this could simply be picking up differences in persistence rates across demographic groups. Looking at the residualized WTPs, netting out the effects of observables, we see that the enrollment rate of students in the lowest tercile of the joint distribution of the WTPs is 97.4%, versus 91.7% for those in the highest tercile. This 6 percentage point difference in enrollment rates is not only statistically significant (p-value = 0.031), but also economically significant. This suggests that our measures are picking up meaningful variation.

5 Conclusions

Using an innovative methodological approach, this paper quantifies the value students place on several key aspects of the college experience, specifically, the value that students assign to in-person instruction and to social life. We find that students' WTP for in-person classes represents 4.2% of the average net cost of attending college, while university-related social activities are valued almost twice as much. We also find large and systematic heterogeneities in the WTP across students, with lower-income students assigning lower valuation to these amenities. In fact, an advantage of our approach is that it allows us to uncover the heterogeneity in preferences under much weaker identification assumptions. We also show that this heterogeneity is meaningful in that it is systematically correlated with the subsequent enrollment decisions of the students.

Our analysis shows that economic and non-economic related covariates play an important role in mediating the socioeconomic gaps in the WTP for social life. For example, students that work more than 20 hours per week – who are disproportionately likely to be from more disadvantaged backgrounds – derive a substantially lower value from on-campus activities. This suggests that constraints may prevent many students from enjoying the amenities that universities provide. It also highlights that college administrators should take into account student heterogeneity in WTP for different school amenities in order to increase diversity on higher education campuses. However, note that while our description of students' preferences for college consumption may be a good representation of the population of currently enrolled students, it is not clear to what extent they can be applied to the college-age population in general. Further work to elicit preferences from the broader population is needed to fully capture the costs and benefits of education policy.

While we find that lower-income and non-white students also have a lower WTP for in-person instruction, these economic and non-economic covariates are unable to explain why students from these groups have a lower valuation for in-person instruction. We are unable to determine if some other constraints (unobservable to us) explain these gaps, or if they are truly due to differences in tastes for mode of instruction. It is also possible that perceived human capital production functions differ across socioeconomic groups. Future work that sheds light on this would be valuable.

Finally, it is worth noting that several things could explain the larger WTP for social activities. First, remote learning likely constitutes a reasonable substitute for in-person classes, while re-creating the university social life in other contexts is likely much more difficult. Moreover, social activities also likely involve the formation of networks which in general are valuable for the students. Future research that sheds further light on the relative importance of university amenities is necessary to fully characterize the value students derive from university attendance.

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Tables

Table 1: Scenarios

	(1) COVID Controlled	(2) In Person Instruction	(3) Normal Campus Social	(4) Vaccine	(5) Avg. Likelihood Return	(6) Median Likelihood Return	(7) Share Not Certain Return (< 100)
Scenario 1	1	1	1	0	89.7	100.0	0.390
Scenario 2	0	0	0	0	80.0	92.0	0.575
Scenario 3	1	0	0	0	84.9	99.0	0.513
Scenario 4	1	0	1	0	87.5	100.0	0.453
Scenario 5	0	1	1	0	75.7	91.0	0.594
Scenario 6	0	1	1	1	85.5	99.0	0.510

Notes: Table characterizes each of the 6 scenarios participants were asked to consider, along with several statistics about the likelihood respondents assigned to returning for the fall semester with costs held constant at previous levels.

Table 2: Summary Statistics

	(1) Survey All	(2) ASU	(3) P-value (1)-(2)	(4) Flagship Univ.[d]	(5) P-value (1)-(4)	(6) Survey Honors	(7) P-value (6)-(2)	(8) Top-10 Univ.[e]	(9) P-value (6)-(8)
Female	0.51	0.48	0.05	0.50	0.70	0.53	0.09	0.50	0.38
Black	0.04	0.04	0.30	0.07	0.00	0.02	0.00	0.07	0.00
White	0.61	0.49	0.00	0.61	0.71	0.60	0.00	0.39	0.00
Hispanic	0.20	0.24	0.00	0.12	0.00	0.13	0.00	0.12	0.66
Int. Students	0.02	0.09	0.00	0.06	0.00	0.01	0.00	0.12	0.00
First-generation[a,b]	0.38	0.28	0.00	-	-	0.20	0.00	-	-
Family Income[a,c]	103	111	0.00	-	-	126	0.00	-	-
Freshman[a]	0.27	0.27	0.53	-	-	0.32	0.04	-	-
Sophomore[a]	0.30	0.24	0.00	-	-	0.38	0.00	-	-
Junior[a]	0.33	0.22	0.00	-	-	0.27	0.05	-	-
Senior[a]	0.10	0.28	0.00	-	-	0.03	0.00	-	-
SAT Verbal 25th %tile	610	532	0.00	548	0.00	680	0.00	711	0.00
SAT Verbal 75th %tile	720	644	0.00	645	0.00	750	0.00	774	0.00
SAT Math 25th %tile	600	542	0.00	556	0.00	690	0.00	733	0.00
SAT Math 75th %tile	750	661	0.00	671	0.00	780	0.00	797	0.00
ACT 25th %tile	25	22	0.00	23	0.00	29	0.00	32	0.00
ACT 75th %tile	32	28	0.00	29	0.00	34	0.00	35	0.00
Sample Size	1,150	60,108		1,339,304		272		81,118	

Notes: Data in columns (2), (3) and (8) is from IPEDS 2018. The flagship universities are the 4-year public universities with the highest number of undergraduate students in each state. Means for these columns are weighted by total number of undergraduates in each institution. ACT and SAT data are weighted averages of 2018-2015 years from IPEDS. P-value columns show the p-value of a difference in means test between the two columns indicated by the numbers in the heading.

[a] Data in the ASU column from a different source. This data includes everyone taking at least one class for credit during the Spring semester of 2018 and attended ASU as their first full-time university. Income and First-generation variables for the ASU data are constructed with the data of the first available year, which is not the first year of college for most of the sample.

[b] Students with no parent with a college degree.

[c] Family income in thousands of dollars.

[d] The largest public universities in each state.

[e] Top 10 universities according to the US News Ranking 2020.

Table 3: WTP Estimates

	N	(1) WTP Social	p-value	(2) WTP In-Person	p-value
All	1,150	1,043*** (116) [8.06%]		547*** (129) [4.22%]	
Lower-Income	513	584*** (129) [4.51%]	0.000	22 (141) [0.17%]	0.000
Higher-Income	637	1,497*** (181) [11.56%]		1,193*** (207) [9.22%]	
First-gen.	436	436*** (130) [3.37%]	0.000	133 (142) [1.03%]	0.001
Second-gen.	714	1,540*** (170) [11.90%]		926*** (193) [7.15%]	
Nonwhite	445	1,011*** (200) [7.81%]	0.833	220 (225) [1.70%]	0.059
White	705	1,063*** (141) [8.21%]		738*** (157) [5.70%]	
Females	582	722*** (172) [5.58%]	0.009	604*** (192) [4.67%]	0.669
Males	568	1,326*** (155) [10.24%]		494*** (173) [3.81%]	
Non-honors	878	885*** (133) [6.83%]	0.004	487*** (146) [3.76%]	0.310
Honors	272	1,657*** (230) [12.80%]		796*** (267) [6.15%]	
Freshman	316	1,414*** (217) [10.92%]	0.043	690*** (251) [5.33%]	0.493
$\geq$ Sophomore	834	895*** (136) [6.91%]		490*** (149) [3.79%]	

Notes: Willingness-to-pay reported in dollars per year. Standard errors in parentheses derived via delta-method. Willingness-to-Pay as a percent of average net costs ($12,948) displayed in brackets. P-value from test of equal WTP between demographic groups. *, **, *** denote estimates are statistically significant at the 10%, 5%, and 1% levels, respectively.

Table 4: Moments of Individual WTP Distribution

	WTP Social							WTP In-Person						
	Mean	Med	StDev	10^{th} P	90^{th} P	%>\$10	%<-\$10	Mean	Med	StDev	10^{th} P	90^{th} P	%>\$10	%<-\$10
All	906 (78)*** [7.00%]	54	2,647	-314	3,092	53.2	19.9	419 (104)*** [3.23%]	0	3,543	-1,704	2,726	45.1	33.3
Lower-inc.	598 (100)***	1	2,273	-303	1,961	48.3	21.4	75 (141)	0	3,197	-1,707	2,076	40.9	35.9
Higher-inc.	1,155 (115)***	154	2,893	-315	3,883	57.1	18.7	695 (150)***	0	3,779	-1,702	4,106	48.5	31.2
	p-val: 0.000							p-val: 0.003						
First-gen.	547 (106)***	0	2,203	-387	2,044	47.2	24.1	204 (121)*	0	2,523	-1,575	2,076	44.0	32.3
Second-gen.	1,126 (107)***	143	2,865	-241	3,702	56.8	17.4	550 (151)***	0	4,037	-1,772	3,483	45.8	33.9
	p-val: 0.000							p-val: 0.109						
Nonwhite	975 (145)***	60	3,053	-521	3,263	54.1	21.8	196 (163)	0	3,432	-1,849	2,525	46.1	34.2
White	863 (89)***	46	2,357	-231	2,889	52.6	18.7	560 (136)***	0	3,607	-1,573	3,209	44.5	32.8
	p-val: 0.486							p-val: 0.090						
Females	833 (109)***	22	2,619	-355	2,902	51.2	21.6	214 (144)	0	3,475	-1,963	2,561	41.9	36.4
Males	982 (112)***	78	2,677	-268	3,158	55.2	18.2	629 (151)***	0	3,602	-1,459	3,210	48.4	30.1
	p-val: 0.341							p-val: 0.047						
Non-honors	811 (86)***	30	2,554	-310	2,840	51.9	20.6	350 (117)***	0	3,454	-1,772	2,561	43.3	34.7
Honors	1,217 (177)***	194	2,912	-333	3,805	57.2	17.7	642 (231)***	24	3,816	-1,684	3,547	51.1	28.7
	p-val: 0.027							p-val: 0.234						
Freshman	1,137 (147)***	168	2,619	-333	4,283	59.8	18.4	467 (207)**	0	3,671	-2,058	3,210	47.8	37.0
$\geq$ Soph.	819 (92)***	12	2,654	-305	2,608	50.7	20.5	400 (121)***	0	3,495	-1,575	2,561	44.1	31.9
	p-val: 0.069							p-val: 0.775						

Notes: Bayesian shrinkage algorithm applied to estimates. Willingness-to-Pay measured in dollars per year. Standard error of mean estimate in parentheses. P-value for equality of means between demographic groups displayed below each set of means. Willingness-to-Pay as a percent of average net costs (\$12,948) displayed in brackets. Within means column *, **, *** denote estimates are statistically significant at the 10%, 5%, and 1% levels, respectively.

Table 5: Correlates of Individual-level WTPs

	(1)	(2)	(3)	(4)	(5)	(6)
		WTP Social			WTP In-Person	
Demographic						
Lower-Income	-378**	-208	-190	-535**	-532**	-527**
	(174)	(172)	(163)	(253)	(261)	(261)
First-gen.	-413**	-241	-237	14	11	29
	(172)	(165)	(169)	(235)	(235)	(235)
Nonwhite	220	160	165	-269	-223	-336
	(181)	(177)	(176)	(220)	(223)	(224)
Female	-3	7	-14	-403	-405	-314
	(198)	(195)	(194)	(245)	(247)	(246)
Honors	247	95	-116	238	127	-103
	(199)	(210)	(227)	(277)	(304)	(346)
Freshman	319*	98	-109	48	-93	-195
	(174)	(172)	(175)	(246)	(245)	(237)
Economic						
Working (0/1)		286	276		-165	-188
		(235)	(230)		(301)	(303)
Work 20+ hrs (0/1)		-524**	-470**		195	339
		(206)	(200)		(314)	(317)
Gross educ. expend. ($1000s/yr)		37***	35***		0	-0
		(6)	(6)		(18)	(17)
Scholarships ($1000s/yr)		-31	-30		10	9
		(19)	(19)		(17)	(17)
Loans ($1000s/yr)		-25*	-24		17	22
		(15)	(15)		(20)	(20)
Gross cost above instate (0/1)		-55	-197		497	462
		(369)	(369)		(470)	(468)
Non-Economic						
Live on campus (0/1)			564***			245
			(218)			(274)
Social events (per week)			61**			-18
			(23)			(37)
Study hrs (per week)			-4			2
			(6)			(9)
ACT (1-36)[a]			6			-1
			(28)			(28)
1+ online/hybrid per sem (0/1)			166			-663***
			(172)			(222)
Other Controls						
College of Major	Y	Y	Y	Y	Y	Y
N	1,149	1,149	1,149	1,149	1,149	1,149
r^2	0.033	0.083	0.099	0.014	0.022	0.034
Mean	904	904	904	419	419	419

Notes: Estimates in dollars per year. Heteroskedastic robust standard errors in parentheses. Gross educ. expend. measures the total expenditure on a student's education from all sources including grants, scholarships, loans, family, etc. *, **, *** denote estimates are statistically significant at the 10%, 5%, and 1% levels, respectively.

[a] ACT scores known for 73.0% of observations. Dummy for missing score also included.

Table 6: WTP Estimates Robustness

	(1) Baseline	(2) Subjective Prob. Scenario > 0	(3) Pass Both Attention Checks	(4) Survey Duration: 5th-95th
WTP Social	1,043***	994***	1,054***	1,006***
	(116)	(123)	(119)	(118)
	[8.06%]	[7.39%]	[8.26%]	[7.87%]
WTP In Person	547***	581***	579***	592***
	(129)	(137)	(133)	(131)
	[4.22%]	[4.32%]	[4.54%]	[4.64%]
N	1,150	1,006	933	1,056
Mean Cost	12,948	13,444	12,753	12,774

Notes: WTP reported in dollars. Sample restricted according to column header. Standard errors in parentheses derived via delta method. WTP as a percent of average cost in brackets. *, **, *** denote estimates are statistically significant at the 10%, 5%, and 1% levels, respectively.

Figures

Figure 1: Perceived Scenario Likelihood

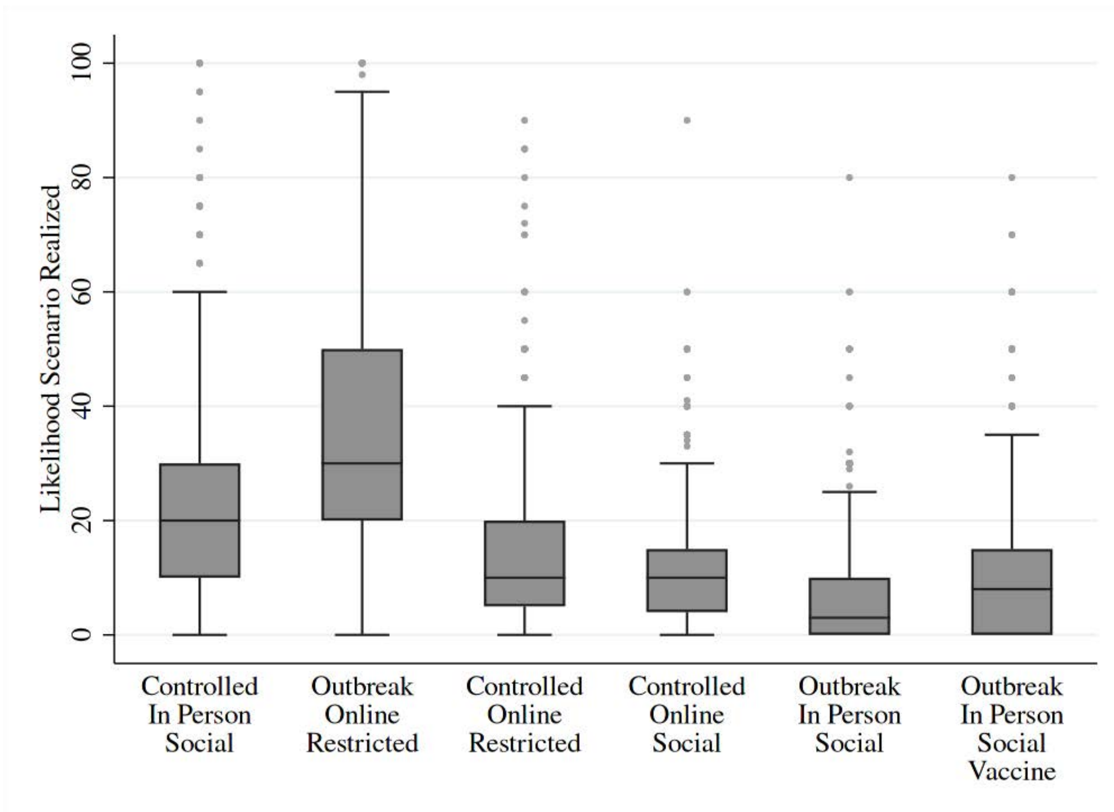


Figure 2: Mean Likelihood Return

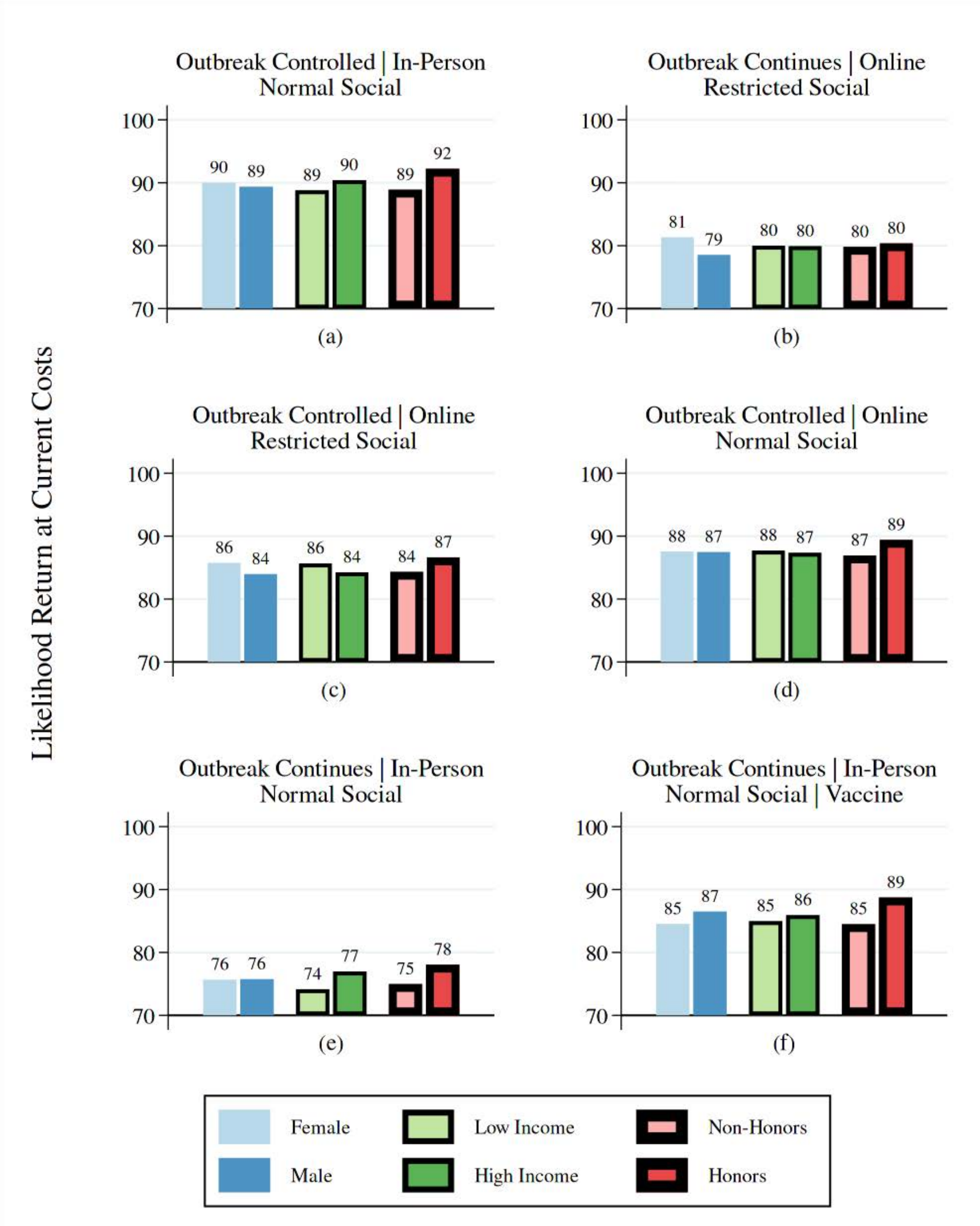
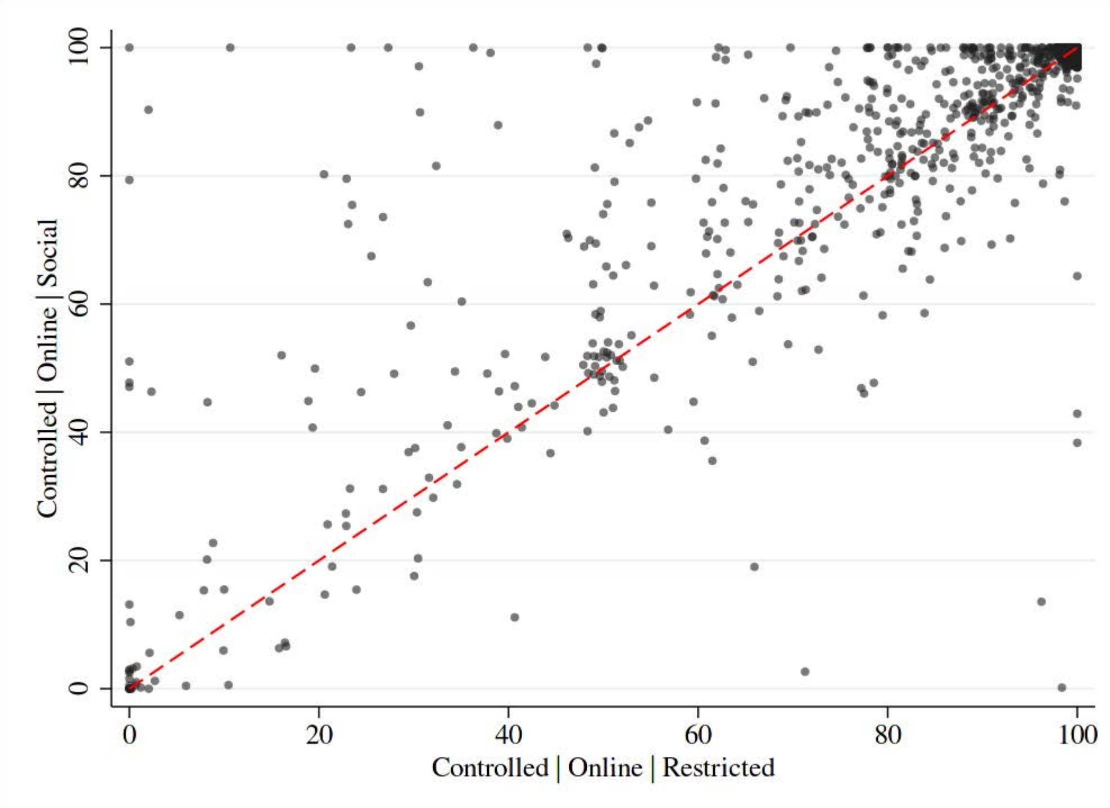


Figure 3: Likelihood Enrolling under Current Prices



Notes: Figure plots the likelihood each respondent would enroll in the Fall 2020 semester if the cost of attendance did not change in scenario 4 against the same likelihood in scenario 3. See Table 1 for description of scenarios.

Figure 4: Stated and Realized Enrollment Decisions

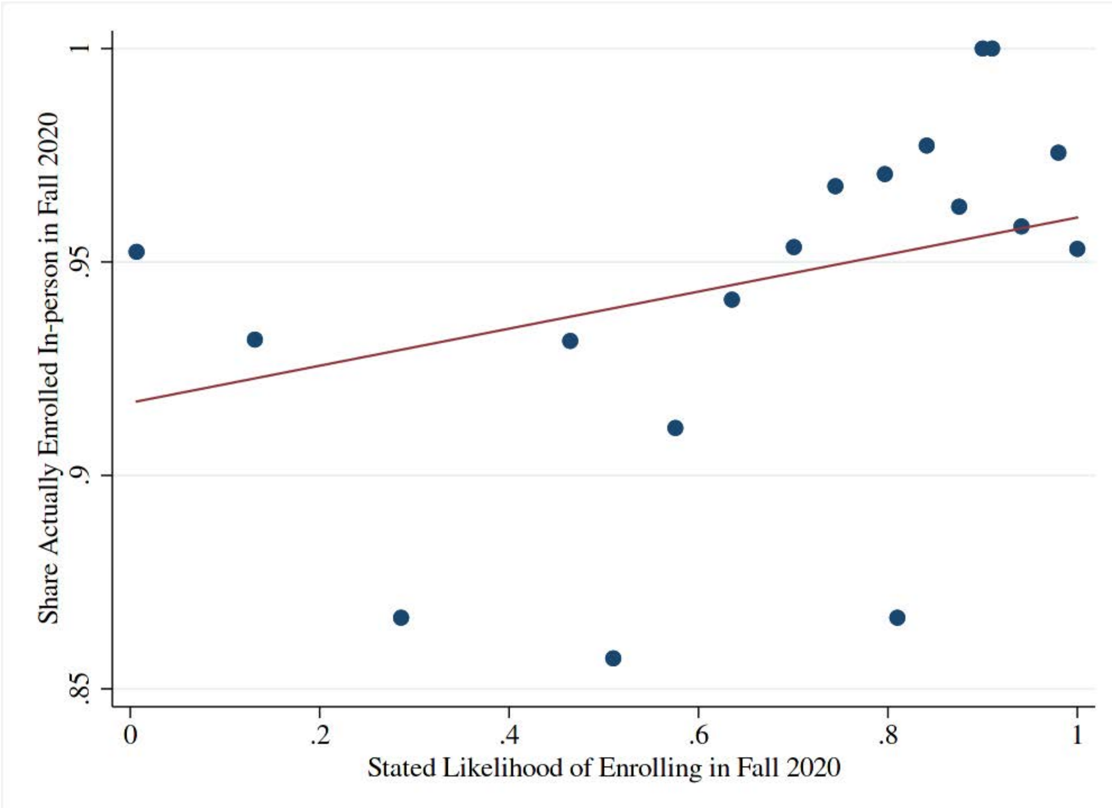


Figure 5: Estimated WTP Cumulative Distributions

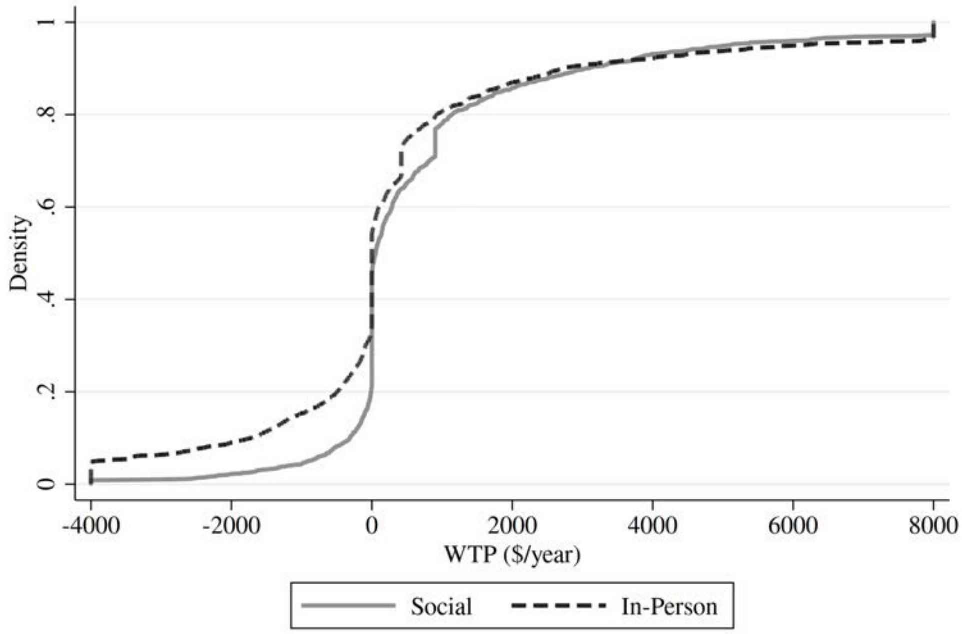
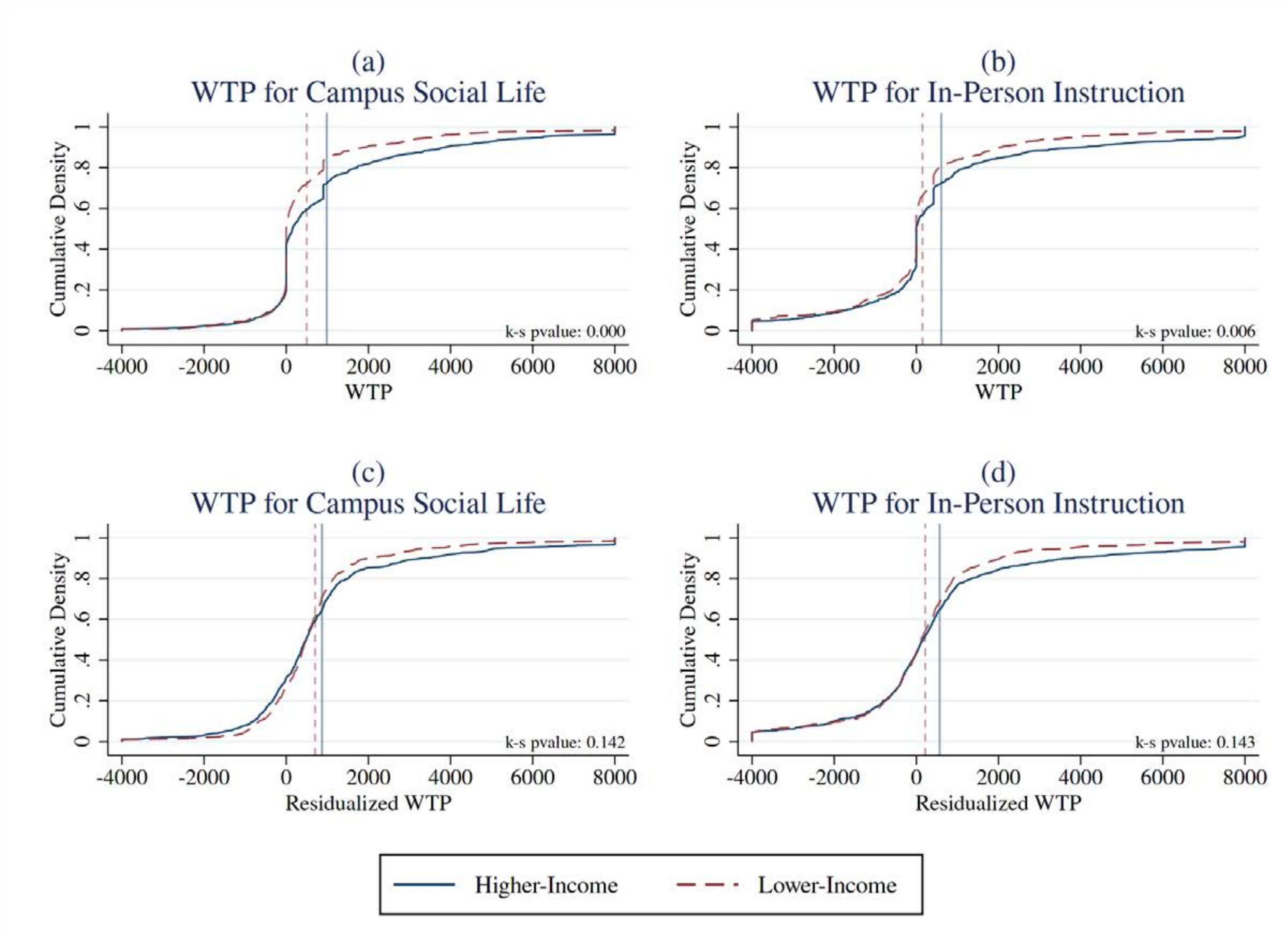


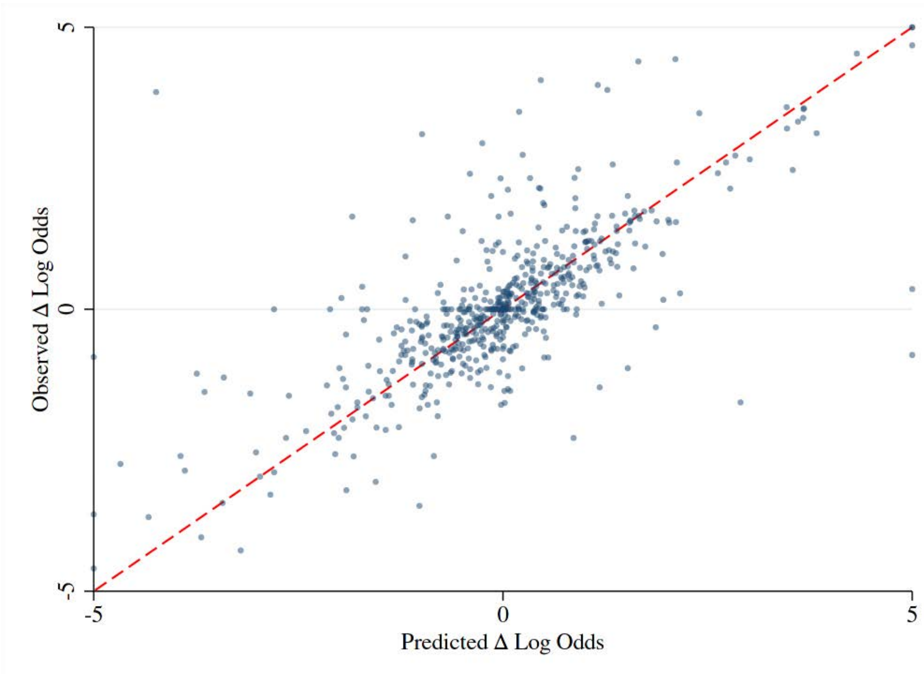
Figure 6: Heterogeneity in Estimated WTP



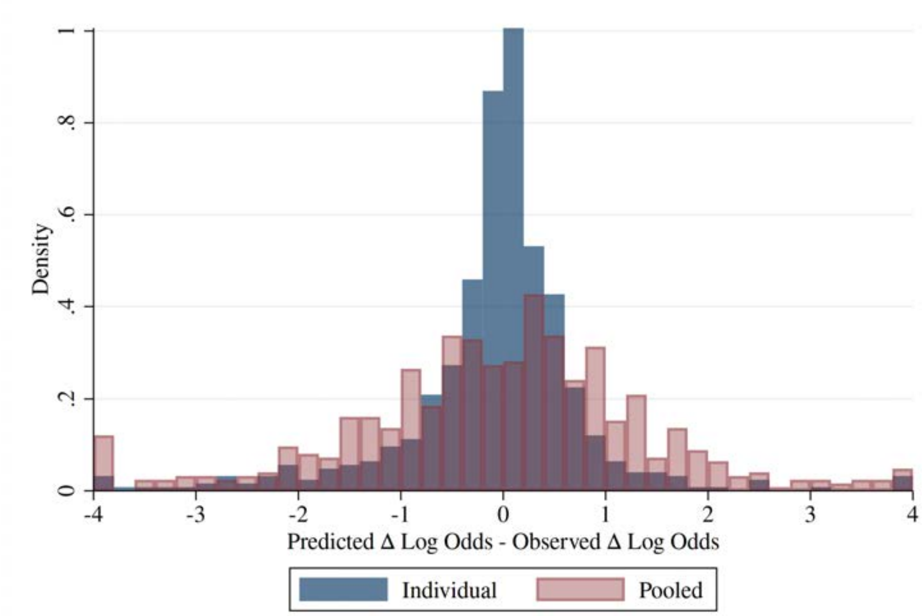
Notes: WTP in panels (C) and (D) residualized against the variables in columns 3 and 6 of Table 5. Vertical lines correspond to mean WTP.

Figure 7: Out of Sample Validation

(a) Validation: Predicted vs Observed Change in Individual Log Odds



(b) Validation: Out of Sample Error Distributions



(a) Notes: 45 degree line in red. Figure plots observed vs. predicted change in log odds for two random scenarios at a random (fixed) cost level. Individual models estimated without the two selected observations and then used to predict change in log odds between these observations. Dropped observations chosen independently across individuals. Observations with stated likelihoods of 0 or 100 lack log odds and excluded from figure. Predicted change in log odds winsorized below -5 and above 5.

(b) Notes: Figure plots the distribution of model error for the change in log odds between two randomly scenarios at a random (fixed) cost level. Selected observations chosen independently across individuals and excluded from estimation procedures. Observations with stated likelihoods of 0 or 100 lack log odds are excluded from figure. Difference below -4 and above 4 winsorized.