Behavioral Dynamics in Transitions from College to the Workforce*

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Abstract

This paper examines how decision-making may change when individuals face a permanent change in financial resources after a major life transition. We experimentally elicit preference and cognitive measures from Colombian students on the job market, as well as from a comparison group of college peers in lower years, over 8 months. This period encompasses the job search process while students are in college and ends after they graduate and begin their full-time jobs. Using a difference-in-differences setup, we find that students entering the job market perceive greater financial liquidity and take on more responsibilities. We do not find any evidence of an increase in the take-up of credit or of students moving out of their parents' homes, features commonly associated with this transition in other countries. Regarding preferences, we find suggestive evidence that the students become less present biased and more prosocial during this transition to the workforce. We do not find significant changes in risk and ambiguity preferences or cognitive performance. These findings help us document the changes experienced during a universal transition, one that is achieved through own effort rather than cash transfers or government policies.

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1 Introduction

Transitions from college to the labor force are both widespread and important events for millions of people every year. Such transitions usually involve a permanent change in income, along with increased responsibilities and more independence from parents or family. In addition, starting a full-time job after college involves choices that may impact on an individual's future quality of life. For instance, high-stakes decisions such as those related to health, retirement benefits, and life insurance are made when starting a first job. Previous research has focused on analyzing the extent to which students smooth consumption before and during this transition (Gustman & Stafford, 1972). Another strand of research examines the stability of preferences across time more broadly and how subjects respond to shocks (for a survey, see Chuang & Schechter, 2015).[1] Despite this, there is very little work documenting and understanding how a universal transition such as the one from college to the labor force may change inputs into decision-making, including economic preferences, prosocial behavior, cognition, and psychological factors.

This paper provides direct empirical evidence on the changes in economic decision-making and psychological well-being in the transition from college to the workforce within the context of college students at a large public university in Colombia. In contrast to previous studies, we focus on a permanent, rather than a transitory, increase in income, and measure other elements of the transition that may change simultaneously with income. Our empirical strategy leverages the fact that we can identify which students will go through the transition, i.e., students in their final semester of college, who are seeking full-time jobs, will graduate and, most likely, start a new position soon after finishing college. As well as recruiting students in their final semester, we then chose students in lower years who were similar in observable dimensions (gender, college major, and economic background) to form a comparison group (henceforth referred to as comparison students) that most accurately mimics behavioral outcomes for final-semester students, had they not finished college.

We target the main periods of the transition from college to the labor force over 8 months during which this change is likely to happen for final-semester students: job search, accepting a job offer, and receiving the first paycheck. We collect our outcomes of interest through four online surveys, two at baseline (April 2016), when final-semester and comparison students are all in college, and two post-graduation (October–December 2016), when final-semester students have graduated and, most likely, have a job offer and have begun receiving paychecks

[1] Standard economic models assume preferences to be constant (Harrison et al., 2005; Dasgupta et al., 2017; Steffen et al., 2008; Roszkowski & Cordell, 2009). However, there is ample empirical evidence that preferences may change when individuals experience an unexpected shock and in response to events or emotions (e.g., Necker & Ziegelmeyer, 2016; Cho et al., 2018; Meier, 2019)

if employed. Our main outcomes include preferences (risk, time, ambiguity, and prosociality), performance in cognitive tests, and survey responses capturing different elements of the transition, including emotional measures. These are measures that would be expected to drive or be highly correlated with real-life decisions that matter during the transition. Examples include how much to save for retirement, whether to buy durable goods, whether to invest in real estate, and so on. At the same time, changes in these outcomes can shed light on potential policies using the timing along the transition to encourage higher savings or greater donations.

We examine changes in economic decision-making, cognitive performance, and psychological well-being using a difference-in-differences strategy (DID). We augment our main DID results with inverse probability weighting (IPW) estimates to match final-semester more closely with comparison students based on observables, and mitigate potential concerns relating to comparison group fit, given the unique seasonality of student life.[2] We present reduced form results, pooling observations from the two post-graduation surveys, and test for the parallel trends assumption using observations from the two baselines.

Our sample may be characterized largely as credit-constrained students, from low- to middle-income backgrounds, the majority of whom overestimate their future incomes. This provides an interesting context within which to study the effect of this transition on various economic outcomes, as this transition (a) represents an increase in income, and a reduction in liquidity constraints, and (b) may be construed as a positive or negative shock, depending on student expectations of future income. Therefore, even though the rise in income may represent a positive income shock, because it may be less than the student's expectations, the effects on risk, time, and social preferences are somewhat ambiguous.

We establish the expectations for each outcome within a conceptual framework. The shift to the workforce may be accompanied by a large change in liquidity or, at least, the expectation of greater liquidity in the near future due to receiving an income from a full-time job. According to our conceptual model, on the one hand, a fall in liquidity constraints may result in lower risk aversion, less present bias, and greater prosociality. However, on the other hand, if income is lower than expected, it represents a fall in perceived liquidity compared with student expectations, which may have the opposite effect on economic preferences. Therefore, it is unclear ex ante if the magnitude of the salary increase in comparison with the expectation is enough to overcome the negative effects of lower-than-expected incomes.

We document four main results. First, of the four dimensions that we hypothesize will

[2]The ideal counterfactual for the final-semester students would be identical students who remain in college but do not experience the seasonality of student life. In the absence of this counterfactual, we believe that the comparison group we chose is a close second.

change in the transition—i.e., perception of liquidity constraints, credit take-up, assuming more responsibilities, and increased independence from parents—we demonstrate that by far the biggest change after graduation is a higher perception of liquidity.[3] While this may seem natural, considering that graduates now have an income or will soon have an increase in their previous income, it helps to identify the presence of credit constraints or other barriers that may have been preventing them from consumption smoothing. On average, the fraction of students reporting difficulty raising emergency funds falls among those transitioning to the workforce. Overall, this represents a decrease of around 25% in the perceived difficulty of obtaining financial resources, compared with a baseline of 59% of comparison students who report difficulties raising cash.

Despite the increase in perceived access to financial resources, students who transition from college to the labor market do not take up more financial products in the short run. For example, they do not report a higher take-up of credit cards or loans relative to the comparison group in the post-graduation period. However, we do observe that they become more responsible for their own expenses, being 8 percentage points (pp) more likely to pay for their own expenses compared with a base of 21% among comparison students. Nevertheless, we do not observe a significant proportion of graduates moving out of their parents' homes, so their increased independence appears to be limited to enjoying a larger flow of income but without undertaking the extra expenditure that finding a new living arrangement would entail.

Second, we find evidence of final-semester students becoming less present biased than their comparison counterparts. We do not capture any differential changes in risk and ambiguity preferences or in performance on cognitive tests. All students, comparison and last semester, become less risk averse and perform better in cognitive tests with time, which we attribute to learning and familiarization with the tasks. Our results are in line with Carvalho, Meier, and Wang (2016), who find that sharp changes in disposable income only affect time preferences, with no observed effects on risk or cognition. These results are also consistent with Angelucci et al. (2017), who study income variations from expected and unexpected shocks, and find only minor changes in preferences and cognition from either source of income change.

Third, students who transition from college to the labor market become marginally more prosocial. We study how students' altruistic preferences change over the transition using a series of dictator games, where the recipient is either another student participating in the

[3] We measure subjects' perceptions of liquidity by asking how hard it would be for them to raise $1,000 for an emergency. We measure increased responsibilities by asking subjects if they pay their own bills and expenses, and independence by whether they live with their parents.

study or a nongovernment organization (NGO) helping poor children in Bogotá. Average contributions in dictator games at baseline in the comparison group are between 30% to 55% of the initial endowment, depending on the recipient.[4] Students who transition to the workforce give about 14% more to NGOs compared with the contributions of students in the comparison group. Even though marginally significant, these effects are relatively sizable when compared with the winners of a lottery in Ethiopia, who give about 7.5% more than lottery losers even though their income increases by a factor of 20 (Andersen et al., 2019).

Fourth, we find large variations across time in an index of negative emotions such as stress, frustration, depression, and worry, although when we examine pooled estimates, the variations are not differentially large for final-semester students post-graduation. Relative to the first baseline measurement, the index goes up by almost 0.4 standard deviations (SD) for all students toward the end of the semester, which may be explained by the fact that there are usually exams at the end of term, resulting in higher levels of stress or worry. After graduation, there is a fall in the index, but it remains at a higher level than the baseline (by 0.2 SD), for both final-semester and comparison students. We conclude that stress or worry appears to be determined largely by seasonality in student life, as well as exam and assignment concerns. When we break down the post-graduation period into two periods (post-graduation 1 and 2), we find that there are some differential effects; final-semester students are differentially less stressed during the first period. However, we are unable to uncover the exact mechanism for this, and the two groups largely follow similar trends.

Our main contribution is to study a setting in which individuals face a permanent increase in their lifetime income. This type of setting is attractive because it captures a more structural, long-run change than the short-run changes in financial resources examined in other studies, such as before or after harvest (Mani et al., 2013), or before and after payday (Carvalho et al., 2016). In addition, our setting is generalizable to a large number of contexts, particularly where students do not have to take on substantial debt to attend college, which is true of several European, Asian, Latin American, and African countries. Furthermore, this setting provides information about changes in behavior in response to a permanent income increase that is a result of effort exerted by subjects, as opposed to cash transfers or other policy-led income increases. However, studying such a large long-run structural change can involve some confounding factors that make it harder to attribute the results to a change in financial status alone. We do our best to document other potential elements arising in the transition and to measure their relative importance. Despite this potential drawback, our

[4] This is higher than the mean allocation of 20% of the endowment that C. F. Camerer (2011) finds in the broader experimental literature and around the average documented by Cardenas and Carpenter (2008) in developing countries.

results imply that long-term decisions made during the transition from college to the labor force may benefit from a less present biased and more altruistic perspective by the decision maker.

The rest of this paper is organized as follows. Section 2 presents the background and research design. Section 3 describes the data collection and experimental measures. Section 4 discusses the econometric strategy and empirical results. Section 5 discusses robustness and attrition, and Section 6 concludes.

2 Background and Conceptual Framework

We study economic decision-making during the transition from college to the labor market for students recruited primarily from the College of Engineering at Universidad Nacional de Colombia, the largest public university in Colombia. There are several reasons for studying these transitions in our setting. First, this university caters mostly to the low- and middle-income population, and its students are likely to experience a larger proportional inflow of resources after graduation relative to richer students. Furthermore, students are charged tuition rates that are monotonically proportional to their family income, as the university subsidizes tuition based on the financial background of students, providing larger subsidies to poorer students. As a result, loans to finance education are uncommon and, because Colombian students live with their families until their late 20s, graduates will likely experience a large and permanent increase in disposable income when they transition to the workforce without the additional costs of moving out from their parents' homes.[5]

A second reason to study transitions in our context is that there is a large degree of homogeneity in terms of ability and college major choice in our sample. Students are admitted to the university based on a common, highly selective college entrance exam and declare their major before enrollment. These features reduce the spread of the ability distribution in our sample and guarantee that participants are capable of understanding study-related experimental tasks, which can be challenging in some developing-country contexts (Cardenas & Carpenter, 2008; Chuang & Schechter, 2015).

Finally, our setting is well-suited to study changes when there is a high likelihood of a permanent increase in income, as most of our students attend the College of Engineering and, hence, have high-paying career prospects.[6] In other words, obtaining a job is a very

[5]There is no established survey measuring the average age when children move out from their family home but press articles suggest that the average age when this happens in Colombia is 27 years. The usual age to start college is 17–18 years, and completing a college degree takes 5 years. In total, 85% of students in our sample are under 27 years of age.

[6]Most students at this college are employed in formal jobs within a year of graduation. According to

likely outcome.

2.1 Sample and Recruitment

To identify the effects of experiencing the transition from college to the labor force, we use the fact that final-semester students experience this transition, whereas comparison students from lower years in the same college will not do so in the short term. However, comparison students may capture some of the unobservable effects of being in college and therefore serve as a counterfactual of what would have happened to final-semester students had they not graduated and transitioned into the labor market. We differentiate between the two groups by calling them "final-semester students" and "comparison students", respectively.

We invited engineering students at this university to participate in a research study about economic decision-making. Students signed up in early April 2016 using an online form containing questions about their demographics, major, current semester in the major, grade point average (GPA), tuition, socioeconomic measures at the household level, whether they worked, and perceived probability of employment between April and October 2016 for those who planned to graduate in August. A recruitment e-mail was sent by the administration to all students (see online appendix 1), and about 95% of our sample is enrolled in engineering. We allowed students from other majors to sign up, as some engineering students forwarded the e-mail to friends in other colleges at the same university.

2.2 Research Design and Descriptive Statistics

The various stages in the research design are summarized in Table 1. We collect data in four waves of online surveys, in addition to a brief sign-up survey. That is, the data are obtained from: (i) a sign-up survey; (ii) two surveys at baseline in April (during the final semester before the graduation of final-semester students); (iii) one survey in October, generally after final-semester students have received and accepted a job offer[7]—which we refer to as "Post-graduation 1"—; and (iv) one survey in December, generally after final-semester students

the US News ranking, the Universidad Nacional de Colombia ranks third among the ranked universities in the country and is the top-ranked public university. According to Colombia's Ministry of Education, in 2017, almost 80% of engineering graduates from this university were employed in formal jobs a year after graduation, and had an average monthly income of 1,858,229 Colombia pesos (COP), or about 620 US dollars (USD). This statistic excludes students who became entrepreneurs or independent workers, or pursued a full-time postgraduate degree. Ministry of Education Statistics can be consulted in the advanced search section at https://ole.mineducacion.gov.co/portal/.

[7]Note that the timing of this survey does not coincide with graduation in August. Because all surveys were conducted either well before or well after graduation, we do not consider that our results are driven by the volatility in emotions associated with graduation.

have commenced their new job and received at least one paycheck —"Post-graduation 2".[8] All surveys except the sign-up questionnaire contained the same tasks, although, in cognitive tests, we varied the questions or worded them differently in every alternate survey to reduce the role of memory. For other tasks, remembering would have been harder as each task involved many choices with the specific values changed for each survey (see Section 3 and online appendix 2).

In Table 2, we provide basic descriptive statistics across these groups. Apart from age and employment-related variables, which we would expected to change as students progress through college, we expect that final-semester and comparison students are similar in most other observed and unobserved characteristics. The two groups have very similar means in their demographic and socioeconomic variables, as well as in their salary expectations upon graduation. Given the more advanced progress in their college career, final-semester students are older and more likely to have accumulated work experience, as expected. On average, final-semester students are in semester 10.41, whereas comparison students are in semester 6.20.[9] However, it is not necessary to observe similar levels in means for both groups. For our DID analyses (in the dimensions of time and student type), it is necessary for the two groups to have similar trends in these measures, an assumption for which we provide empirical support in the form of parallel pre-trends.

2.3 Creating a Comparison Group

To create our sample, we first screened and counted how many final-semester students signed up. Our pool of lower-year students was much larger. Therefore, we selected the number of lower-year students to equal the number of final-semester students. We did so by stratifying on gender, major, and tuition above or below the median.[10] To elaborate, we created cells based on these three observable characteristics and placed students in lower semesters in the cells to match the number of final-semester students. For example, if there were five female final-semester students in mechanical engineering with tuition below the median, we would randomly pick five females in lower years in the same major and tuition range among the pool of students who signed up for the study. Our resulting number of observations or students at baseline is 365, of which, 179 (49%) were in their final semester.

[8]Some final-semester students had either received a paycheck by the time that we administered the Post-graduation 1 survey or never reported receiving a paycheck, despite indicating that they had received a job offer.

[9]As a rule, engineering majors have a length of 10 semesters or 5 years. It is not uncommon to take one or two additional semesters to graduate if students take longer to finish their graduation requirements or if they fail a core subject that is prerequisite to others.

[10]The median tuition per semester in our sample is 600,000 COP, which was equivalent to around 200 USD based on the exchange rate at the time that the recruitment took place.

Finding a suitable counterfactual for final-semester students was challenging. However, we consider that lower-year students comprise the best possible comparison group feasible in this context. This is not without some disadvantages. For instance, survey responses by comparison students may plausibly be affected by the timing of examinations or other academic events. In Section 4, we discuss whether observed results may be driven differentially by the experiences of comparison students. To gain a better understanding of what would be expected to affect the behavior of comparison students, we provide a summary of the 2016 academic calendar in Table 1. The dates assist in understanding when such students may experience more or less stress at different points of the semester, e.g., when final exams take place.[11] Final-semester students generally do not have exams in their last semester, but may have to submit final drafts of projects or complete certain requirements for graduation before the end of the semester.

2.4 Conceptual Framework of the Transition from College to the Workforce

To formalize and understand the mechanisms behind our hypotheses, it is helpful to think of the subjects as belonging to one of three possible categories. One group has accurate expectations about their future incomes, given that their income change is expected, and they fully internalize the effects of the impending transition. The second and third groups are those who, respectively, underestimate and overestimate their future incomes relative to their initial expectations. For brevity, we refer to these groups as pessimistic and optimistic, respectively.[12]

All three groups may smooth consumption and have stable preferences (Harrison et al., 2005; Dasgupta et al., 2017; Steffen et al., 2008; Roszkowski & Cordell, 2009), but differ in how accurate their expectation of future income is relative to realized income. In the case of the group that accurately predicts future income, we do not expect changes in their preferences because they fully internalize the changes that the transition will bring about and respond to the experimental tasks accordingly. Although pessimistic and optimistic students expect an increase in income, there is a component of the increase that is unexpected. This unpredicted component may affect students' psychological well-being and lead to changes in economic preferences (Meier, 2019). This is not an unusual characterization of these students'

[11] The university does not have a fixed date at which midterm exams are scheduled. Each instructor determines the number and timing of the exams or assignments that students need to take or submit. However, it is common to have final exams or papers due near the end of the semester.

[12] It should be noted that the terms "pessimistic" and "optimistic" are not meant to represent groups with irrational preferences; they may have rational preferences but simply obtain better or worse paying jobs than expected.

expectations based on informal interviews about their expectations for the job market. In fact, using data from initial salary expectations and realized salaries post-graduation (Figure 1), we can perceive the three groups in our sample. In particular, large groups of students underestimate and overestimate their future salaries, with a minority being accurate about their expected income.[13]

Expected responses vary for each of the above-described individuals. First, in instances where individuals predict their incomes perfectly, the transition can be interpreted as resolving potential credit constraints. There may be very limited changes in preferences or emotions, as these changes may have already been internalized. The relaxation of credit constraints would be expected to affect perceptions of liquidity positively, given that students still experience an income increase. Second, for individuals who are either pessimistic or optimistic, we may expect different outcomes based on whether these individuals live in a credit-constrained world. Both groups may display changes in their perception of liquidity, independence, emotional measures, prosociality, and economic preferences because of the component of income that is unanticipated.

The pessimistic group may underestimate the probability of getting a job. Therefore, when they do obtain jobs and receive paychecks, their perception of liquidity and independence increases because they did not fully account for the potential pay increases, particularly in a credit-constrained environment such as this. Therefore, we may expect that a transition that increases income by an unanticipated amount may generate positive emotions for pessimistic students, which in turn, reduces their risk aversion and present biasedness (Meier, 2019). More directly, income changes or changes in wealth may be associated with changes in risk aversion Guiso and Paiella (2008).

The optimistic group may still perceive an increase in liquidity relative to the counterfactual of them remaining in college and not starting permanent jobs, even though their income may be lower than expected. However, receiving a lower income than expected or facing more difficulties finding a job than anticipated may trigger negative emotions despite the increase in income, so the overall effect depends on which of these two is stronger.

Similarly, the effect on prosociality may not be clear. Previous work has established that the rich give more than the poor (for a review, see Andreoni & Payne, 2013). More recent work has shown that the rich give more when the endowment is fixed across socioeconomic groups, but give a similar fraction of their endowment when it is adjusted to the subjects'

[13] We thank an anonymous referee for pointing out that a fraction of the transitions observed may involve students shifting from part-time to full-time jobs within the same firm. In this case, it is easy for students to align their expected and realized incomes correctly. We do not, unfortunately, have any data on within-firm transitions. In our surveys, we ask students directly what they expect in terms of income when they begin their full-time jobs and compare this with what they actually receive when they start working.

actual income level, suggesting that the rich give more because they can afford to (Blanco & Dalton, 2019). If giving is a normal good, it will increase in response to the increase in income. However, if realized income is below expectations, students may not give more because they experience the income increase as a negative shock compared with their expectations.

2.5 Characterization of the Transition

Now, we provide evidence that students in our sample are most likely to be credit-constrained. In Colombia, students cannot perfectly smooth consumption by taking loans to keep their standard of living constant before and after graduating from college. In our sample, only 6% of students have credit cards with a credit limit above $1,000 (the equivalent of about 1.5 times the expected monthly salary in their first job after graduation) and about 10% have loans over $5,000 at baseline. Not only is it difficult to obtain a credit card, but also there is also a cultural lack of comfort with the use of credit cards. Credit card penetration is low and people prefer to pay in cash (Correa et al., 2018). Therefore, there are both administrative and cultural barriers to borrowing for consumption smoothing and we may expect changes in our outcomes when final-semester students go through the transition.

Another feature of the transition is that many students hold part-time jobs during college, but only a small minority hold full-time jobs. A significant fraction of students are from low socioeconomic backgrounds and these jobs help them cope with living expenses. Therefore, this transition from college to the labor force may be characterized as moving from largely part-time to full-time work. Figure 4 shows the rates of both part- and full-time work among students. These graphs demonstrate how an increasing number of final-semester students transition into full-time employment from the baseline to the post-graduation periods. Despite the specificities of the Colombian context, a widely generalizable feature of this transition is this very increase in full-time employment rates among final-semester students, which is accompanied by a large increase in salary. Figure 2 shows a marked rightward shift in the density function of the salaries received by final-semester students going from the baseline period to post-graduation.[14]

Therefore, our sample may be characterized as consisting largely of credit-constrained people, from low- to middle-income backgrounds, most of whom overestimate their future incomes. Therefore, even though the rise in income may represent a positive income shock,

[14]A number of students do not secure jobs by the time of the last survey. We examine the data in two ways: by treating their salaries as zeros, and by leaving their income as missing in the data set. Figure 5 shows the mean salaries of final-semester and comparison students both with and without zero salaries. In both panels of the graphs, the transition towards higher salaries among final-semester students remains clear, and is both large and significant. We also plot densities of salaries in Figures 2 and 3 at baseline and post-graduation. We drop two students at the top percentile who have implausibly high salaries.

because it is less than the students' expectations, the effects on risk, time, and social preferences are somewhat ambiguous. It is ex ante unclear if the magnitude of the salary increase in comparison with the expectation is enough to overcome the negative effects of lower-than-expected incomes. Given the average characteristics of subjects in our sample, the reduced form DID results may be informative about which effect is larger.

3 Experimental Tasks

3.1 Tasks and Incentives

We administer a series of tasks for students to complete in each of the four online surveys. Our surveys contained three types of questions: economic decision-making tasks, social preferences, cognitive tests, and questionnaires about socioeconomic situation, debt and credit, stress, and salary expectations. In addition, to build a timeline, we ask final-semester students about when they anticipated job offers and paychecks. We follow previous studies (Carvalho et al., 2016) in the design of these tasks and provide details below. The order in which tasks appeared to participants was randomized, although they always came before the questionnaire about psychological and stress measures, expenditures, salary expectations, and relevant dates for receiving job offers and paychecks. No feedback about performance was given to the participants. Further details on the tasks can be found in online appendix 2.

To ensure incentive-compatible compensation for study subjects, a task was picked at random after every survey, and a payment was assigned as per the students' choices or performance, following Azrieli, Chambers, and Healy (2018). The computer followed the instructions communicated to the participants regarding the rules for earning money in each task. For instance, if the computer chose the risk-aversion task, the gamble picked by the student was played and they were paid accordingly. Such a payment structure incentivizes students to reveal their choices truthfully and to exert effort to maximize performance. The mean prize across all three rounds of surveys was $36 (around $12 in each stage). To indicate how much this represented to students, $30 would pay for about 40 bus tickets or restaurant meals for 2 weeks. See online appendix 1.3 for details.

Risk Preferences: We elicit risk aversion using the Eckel and Grossman (2002) measure. Students pick one gamble to play from a list of six gambles, and their choice indicates their degree of risk aversion. We obtain the lower bound of the implied constant relative risk aversion (CRRA) of each of these gambles and use this as our measure of risk aversion (see implied CRRA ranges in Charness et al., 2013).[15] Risk-averse students should choose a gamble between 1 and 4 with a low SD, whereas risk-neutral students should choose gamble 5, which has a higher expected return than the first four gambles, and the same return but a lower variance than gamble 6 (see Table 1 in Charness et al., 2013).

Time Preferences: We adapt the elicitation task presented in Andreoni and Sprenger (2012). Subjects are given a pre-specified monetary amount and are required to allocate it between two dates, referred to as sooner and later. In contrast to Andreoni and Sprenger (2012), subjects allocate the endowment of 50,000 pesos ($17) in increments of 1,000 pesos rather than using continuous values. Given administrative constraints, our earliest sooner period means that students receive a payment 1 week after responding to the survey. Thus, we do not have immediate rewards. We study how the amount allocated to the sooner period changes along the transition. Online appendix 2.4 provides more details.

Ambiguity Aversion: This is the preference for known risks relative to unknown risks (Ellsberg, 1961; C. Camerer & Weber, 1992), and is measured using a task based on Tanaka et al. (2014), in which subjects must choose between a gamble for which the outcomes' objective probabilities are known and one in which they are unknown. Our participants are shown two urns containing red and blue balls and must choose one of the two urns. In ambiguous urns, the exact color composition of the balls is unknown because part of the urn is covered. Participants receive a payment depending on the color of a ball selected at random from the urn that they choose. Online appendix 2.3 provides more details.

Social Preferences: We administer a set of dictator games, where subjects choose to allocate a portion of two endowments of 20,000 pesos ($7) each to: (i) another participant in the study, and (ii) an NGO that helps children in Bogotá. Online appendix 2.1 provides more details.

Cognitive Tests: In terms of cognition, the bandwidth theory proposed by Mullainathan and Shafir (2013) implies that scarcity (of time or resources) affects cognitive functioning, which may compromise decision-making (Shah et al., 2012; Mani et al., 2013; Mullainathan & Shafir, 2013). To measure different dimensions of cognition, we use tasks such as a Raven's matrices-type IQ test, the cognitive reflection test (CRT), Flanker's task, and the numerical Stroop test. Online appendix 2.5 has more details.

[15]The values of the CRRA we use are for each of the six gambles are 3.46, 1.16. 0.71, 0.50, 0, and –1, respectively. Because gamble 6 has no lower limit, we obtain the average growth of lower limits from gambles 1 to 5 and apply it to gamble 6.

4 Difference-in-Differences Results

To examine whether the economic and social preferences, cognitive performance, and survey responses of our sample students change along the transition from college to the labor market, we employ a DID strategy. We are interested in changes after graduation when final-semester students will most likely receive a job offer, start working, and receive at least one paycheck, relative to a baseline where all participants are college students. Even though the transition may be anticipated, students may overestimate or underestimate their future salaries or the kind of job that they will end up with. Our data collection in the post-graduation 1 period was intended to capture the effects of uncertainty around job details being resolved. The post-graduation 2 period was intended to capture how responses change when final-semester students receive a paycheck. In practice, this distinction proved challenging because of great heterogeneity in the timing of these two periods for different participants. Therefore, we do not distinguish between these two stages in our analysis. We refer to them together as 'post-graduation' and pool the two stages.

To examine the effects of the transition from college to the labor market, our main DID regression specification is as follows:

$$y_{it} = \alpha_1 + \alpha_2\ Baseline\ 2_t + \alpha_3\ Post_t + \beta_1\ Final\ sem_i + \beta_2\ (Baseline\ 2_t \times\ Final\ sem_i) + \beta_3\ (Post_t \times Last\ Final\ sem_i) + \gamma_k + \rho X_i + \varepsilon_{it} \quad (1)$$

In the above specification, y_{it} includes our outcomes for individual i across t periods, which comprise two baselines and a post-graduation period (pooling post-graduation 1 and 2 periods). Indicators for these periods are labeled *Baseline* 2 and *Post* in the econometric specification. The constant in this regression provides the mean of the comparison group at Baseline 1 (the first data collection of outcomes). The rest of the α coefficients give the difference in the means for the comparison group across rounds. The coefficient β_1 reflects the difference in means between final-semester students and the comparison group at Baseline 1, β_2 provides a test for the parallel trends assumption, and β_3 is the pooled DID coefficient measuring our effect of interest. We control for the baseline characteristics in Table 2 (X_i), and add cell fixed effects (γ_k) for each of the cells containing gender, major, and tuition level details, from which the comparison group was built. We cluster standard errors at the individual level to account for correlation in the residuals across time.

In addition to the above estimates, we present IPW estimates to mitigate concerns related to the suitability of the comparison group. We follow Abadie (2005), who proposes a weighting scheme that gives larger weights to individuals in the comparison group who are more similar in observable characteristics to individuals in the final-semester group. The weighting scheme is based on the propensity score $P(\text{Final-sem} = 1|X)$, which is estimated in a first step.[16] This function contains the following characteristics: gender, engineering program, GPA, socioeconomic background (measured with residential strata and a poverty measure), tuition bin, number of semesters employed at baseline, and expected first salary after graduation. The two assumptions for this methodology are that, conditional on the covariates, the average outcomes of both groups would follow parallel trends in the absence of the treatment, and that there is common support in the propensity score.

Under the two assumptions, the average effect of the treatment on the treated is a weighted average of the temporal differences in the outcome, in which the weights are given by the propensity score. By weighting down the distribution of temporal differences for values of the covariates that are overrepresented among the untreated, and weighting it up for values that are underrepresented, the same distribution of covariates is imposed for both groups (Abadie, 2005). We prefer this methodology for matching over other conventional alternatives, such as nearest-neighbor matching, as we have longitudinal data with repeated observations for the same individuals (which is the type of data to which the Abadie (2005) method is best suited), and our sample is small.

4.1 Features of the Transition from College to the Workforce

Securing a job and being paid may affect job seekers' perceptions of their liquidity, creditworthiness, ability to take up financial responsibilities, and independence. We analyze how the perceptions of access to liquidity and the take-up of financial products change during the college-to-labor-market transition.

In Table 4, we show the results of the pooled DID and IPW regressions on outcomes such as whether it is hard for students to raise \$1,000 for an emergency and whether they have credit cards or loans. In Table 5, we show whether they pay for most of their expenses (responsibilities) and whether they live with their parents (independence). Receiving a job offer and obtaining a paycheck has a significant and positive effect for final-semester students. Our findings suggest that they perceive an increase in access to financial resources. The fraction of final-semester students reporting that they would have to do something drastic to raise \$1,000 for an emergency or that they would not be able to raise this amount at all is reduced by 14 pp when compared with students in lower years (column 1, Table 4). These reductions can be compared with the baseline of 59% of comparison students reporting

[16] The estimator proposed by Abadie (2005) is $E[Y^1(1) - Y^1(0)|D = 1] = E[\frac{Y(1)-Y(0)}{P(D=1)} \cdot \frac{D-P(D=1|X)}{1-P(D=1|X)}]$, where D corresponds to our final-semester indicator. Because this estimator requires the change of the outcome of interest between baseline and follow-up, we compute this as the difference between the mean outcome value of post-graduation periods 1 and 2, and the mean outcome value over Baselines 1 and 2.

that they would have to do something drastic to raise \$1,000 for an emergency or that they would not be able to raise this amount at all.[17] Column 2 of Table 4 presents the IPW estimates, which have a similar magnitude. The DID and IPW estimates remain significant after adjusting for multiple hypothesis testing using the family of outcomes in Tables 4 and 5.

Column 3 of Table 4 shows that even though there is an increased perception of access to resources, we find no evidence that students transitioning to the labor market differentially take up products such as credit cards or loans. Final-semester students are slightly more likely than comparison students to have credit at baseline, but there is no differential increase in take-up during the transition to the labor market. These findings could be explained by students not having to ask for loans to pay for college, as their tuition is subsidized based on the socioeconomic background of their household. In addition, in Colombian culture, as noted above, students do not move out of their parents' home during or immediately after college, which suggests that they would not need credit to set up a new living arrangement. We provide evidence that it is relatively uncommon for students not to live with their parents, as only about 5% of students do so, and that final-semester students are not differentially moving out of their parents' homes, as shown in columns 3 and 4 of Table 5.

Finally, students in their last semester of college take up more financial responsibilities at baseline and continue to increase this level differentially as they transition to the labor market, with an increase of 8 pp (column 1) or 11 pp with the IPW estimate (column 2) over bases of 21% and 36%, respectively, as shown in Table 5. As shown in column 2 of Table 5, the IPW estimates are larger in magnitude and remain significant at the 10% level after adjusting for the false discovery rate (FDR).[18]

These results quantify various characteristic changes in the transition from college to the labor market and provide us with the magnitude for these changes. These magnitudes may be helpful in future applied work when describing this transition into the labor force.

4.2 Economic and Social Preferences

Experiencing temporary shocks or major life events can affect individuals' preferences. Chuang and Schechter (2015) provide a multidisciplinary review of the impacts of events such as economic shocks, natural disasters, and conflict on risk, time, and social preferences. Their main

[17] See survey questions and variable coding in online appendix 2.6.

[18] We did not ask some of the questions included in these tables at Baseline 1, which means that there is no coefficient for Baseline 2 in the DID results. However, most of these variables are unlikely to change in a matter of days or weeks, which was the time frame between the two baselines. For example, it is very unlikely that students would move out of their parents' homes in such a short time period. For this reason, we are not concerned about violations of the parallel trends assumption.

finding is that the literature has not achieved a consensus on the direction of the effects or on whether there are any effects at all. We add to this literature by studying an anticipated event that involves, among other things, a large change in the level of individual income.[19]

Many important economic decisions such as which type of health insurance and pension contribution scheme to select are made during the transition from college to the workforce. These decisions may be shaped by how risk averse or present biased an individual is. In this sense, another line of research to which our work is connected to is the literature studying the effect of temporary changes in income on risk and time preferences (e.g., Haushofer & Fehr, 2014; Haushofer, Schunk, & Fehr, 2013; Carvalho et al., 2016; Angelucci et al., 2017), and that on giving in dictator games among people of different income levels (Andreoni & Payne, 2013; Blanco & Dalton, 2019). Most of the papers in these strands of the literature focus on temporary rather than structural changes, or on preexisting differences in socioeconomic status.

4.2.1 Risk and ambiguity aversion

Conceptually, risk and ambiguity preferences may change as individuals age in response to shocks such as economic crises or natural disasters, or as a result of temporary variations in self-control, emotions, or stress (Schildberg-Hörisch, 2018; Meier, 2019). Carvalho et al. (2016) argue liquidity constraints and scarcity are potential factors affecting risk aversion before and after receiving a paycheck.

To measure risk aversion, we elicit the preferred gamble from the six proposed in the Eckel and Grossman (2002) task and obtain the lower limit of the CRRA as our main outcome. The possible CRRA values range from 3.46 for the most risk-averse individuals to −1 for the most risk-loving individuals. Hence, reductions in the CRRA would mean that individuals become less risk averse. The ambiguity aversion variable counts the number of times that the ambiguous urn is chosen out of nine possible choices, ranging from the fully visible to the more ambiguous urns, as in Tanaka et al. (2014). Higher values in this outcome reflect participants' willingness to choose more ambiguous options.

Table 6 shows the results for the risk and ambiguity outcomes. The parallel trends assumption is satisfied for both outcomes, as the interaction between Baseline 2 and the last semester is statistically insignificant and close to zero. On average, all students are risk averse at baseline, with a CRRA of 1.12, which is borderline between choosing the second and third most risk-averse gambles in the list of six. After graduation, the CRRA goes down

[19] One important methodological advantage with respect to the literature studying extreme events is that we can build a comparison group based on observable characteristics and collect data from both groups of students before the transition takes place.

by about 0.45, or 40%, but there is no differential effect for final-semester students.

The ambiguity aversion results (columns 3 and 4 of Table 6) show that, at baseline, students chose the ambiguous urn in about one third of the nine choices. After graduation, students become less ambiguity averse, choosing 0.56 more ambiguous urns. However, we observe no differential impact of being a final-semester student, and we do not see any difference between the intent-to-treat (ITT) or IPW results.

4.2.2 Time preferences

We deviate slightly from the specification we use elsewhere in the paper to follow closely Carvalho et al. (2016), who use a time-preference elicitation task similar to ours. The task consists of 16 choices, where the respondent is asked to allocate an endowment equivalent to 17 USD to a sooner and a later date. We vary three dimensions: the duration between the two payments (4 vs. 8 weeks), when the sooner payment is received (in 1 week or in 5 weeks), and the interest rate payable on the amount allocated to the later date (1%, 10%, 50%, or 100%). Our outcome is how much of the endowment is allocated to the sooner period. In addition to the interactions between the period variables and the final-semester indicator, we add triple interactions with the three features (delay, sooner reward in 1 week, and interest rate) that we vary in the task.

Table 11 presents the results for the amount allocated to the sooner period. For readability, we do not show the interactions with the Baseline 2 indicator, but the full regression results show that the parallel trends assumption holds. The first two columns in the table include all students and show the ITT and IPW results. Columns 3 and 4 show the results for the subset of students who responded to the comprehension questions correctly.[20] At baseline, participants assigned about 35% of the endowment, or around US$6, to the sooner period. As expected, they allocate less to the sooner period when the interest rate is higher (US$2.18) and more to the sooner period when the delay between the sooner and later period is longer (US$1.22). In contrast with previous findings, we find that when the sooner period is 1 week away (the earliest that we promised to pay), the students allocate less money to that period (US$0.80). The literature finds that with an immediate reward, individuals tend to disproportionately assign more money to the sooner period. In our case, however, they have to wait 1 week to receive the amount, which may explain why students may not exhibit the usual present biasedness.

Table 11 shows that in the post-graduation period, comparison students are more present biased—they allocate US$2.67 more to the sooner period than they do at baseline. Under

[20]Given that this was the most involved task, we added four practice questions based on an example to ensure that the participants understood how much they would earn under a hypothetical scenario.

the ITT specification, there is no difference between the behavior of final-semester and comparison students post-graduation. However, the IPW estimates indicate that final-semester students are less likely to exhibit present biasedness after graduating by between US$0.66 and US$1.01, depending on whether we condition on task comprehension. This result holds for the triple interaction coefficients, except for the interest rate, which suggests that when the interest rate increases, the effect reverses slightly. Our IPW estimates are similar to Carvalho et al. (2016), who find that, before payday, poor individuals in the US are more present biased when making choices about monetary rewards. In our case, when students have moved along a transition that entails a substantial increase in (perceived) liquidity, they behave in a way that is less present biased. However, given that the ITT does not give the same result, this evidence is merely suggestive.

4.2.3 Social preferences

We use two dictator games to measure final-semester and comparison students' prosociality. We provide students with two endowments of 20,000 pesos ($7) each and ask them to donate to another student participating in the study using one of the endowments, and to an NGO using the other. Each of these endowments, and subsequent donations, constitutes a single game. Students play these two games four times in total across all the stages of the study design. At the end of each survey, one of the tasks (including economic preferences and cognitive tasks) is randomly selected for payment. If one of the dictator games is selected, the participants receive the amount net of the value of their donation.

Table 8 presents the pooled DID estimates, with columns 1 and 3 showing estimates for the fraction of endowment donated to another participant and NGOs, respectively. We do not detect any significant increase in giving as final-semester students transition to the labor market. However, when considering IPW estimates, there is an increase in NGO donations among final-semester students after they graduate and start their permanent jobs. The increase in NGO contributions is about 14% over comparison students. Compared with the average donation in dictator games in experimental economics of around 20% of the endowment (C. F. Camerer, 2011), all students in our sample donate higher proportions of their endowment, and final-semester students give differentially more to NGOs as they go through the college to labor force transition. These differential results are comparable to other documented changes in income. For example, people who win a housing lottery in Ethiopia give about 7.5% more to a charity than do lottery losers in a modified dictator game, even though the lottery winners experience a 20-fold net income increase (Andersen et al., 2019). In our case, relative to the comparison group, the average income for final-semester students increases between 5.7 and 6.9 times when comparing baseline with post-graduation, respectively. It is possible that the increase observed reflects the characteristic of donations as a normal good. As noted above, the literature on generosity and wealth has established that the rich give more than the poor in general (Andreoni & Payne, 2013; Blanco & Dalton, 2019).

4.3 Cognitive Performance

Previous work in behavioral development economics has shown mixed results regarding the effect of poverty on cognition. While Mani et al. (2013) find changes in Raven's test performances among sugarcane farmers before and after receiving payment from harvest, Carvalho et al. (2016) do not find changes in the cognitive tasks they administer (which do not include the Raven's test) before and after receiving a paycheck. To understand why changes in the performance of cognitive tasks may occur, the bandwidth theory proposed by Shah et al. (2012) posits that scarcity of time or material resources takes cognitive resources from the brain and leaves less working memory to be used in decision-making. Other studies argue that when individual resources for self-control are low, the risk-averse short-term self may prevail over the deliberative risk-neutral long-run self (Fudenberg & Levine, 2006, 2011; Fudenberg, Levine, & Maniadis, 2014). Because finding and starting a new job may affect cognitive and self-control resources, in this section, we investigate whether any changes in cognitive performance can be observed across the transition from college to the labor force.

We study changes in cognitive performance by examining how students perform in tasks, including the Raven's matrices, CRT, the Flanker task, and the Stroop test. We combine student performance in these tests into an index of cognitive performance (columns 3 and 4 in Table 9). We build this index by standardizing each individual component and then taking a simple average and standardizing again (Kling, Liebman, & Katz, 2007).[21] In column 3, we show the DID estimate for an index averaging the standardized versions of these tests and find parallel trends in the index. The performance of all students in the aggregate index and most other tests improves over time, which may be attributable to learning effects. However, there is no difference between the performance of final-semester and comparison students across stages. Our results are in line with the findings of Carvalho et al. (2016). Figure 7 shows the results by separating the Post-graduation 1 and 2 periods. It is evident from the graphs that there was no significant difference in performance between final-semester and comparison students. We administer two versions of the test: one version at Baseline 1 and Post-graduation 1, and another at Baseline 2 and Post-graduation 2. We do this to avoid the role of memory in performance, particularly as the two baseline rounds

[21]The standardization is computed based on the mean and SD of the measure for comparison students at baseline.

are 1 week apart. This difference in tests accounts for the different average scores across test versions.

4.4 Psychological Measures

An important dimension of significant life transitions, albeit frequently understudied in economics, is the psychological state of people experiencing the transition. For example, finding a new job can bring excitement and a more positive outlook for the future. With the aim of documenting the changes in the psychological dimension, we focus on four main negative emotions that can be associated with the transition from college to the workforce: stress, frustration, depression, and worry. We use standard measures including Cohen's Perceived Stress Scale (PSS) (Cohen et al., 1994) and other self-reported measures of subjective well-being used in Carvalho et al. (2016).[22]

We create a summary index by taking the average of the standardized variables in Table 9 (Kling et al., 2007) and present evidence of parallel trends for the index. We do not observe any significant differential changes in the stress index among final-semester students as they enter the job market. However, there are a few important observations to be made from this table. The levels of negative emotions across both final-semester and comparison students are higher than the Baseline 1 levels when the students are at Baseline 2 and Post-graduation by 0.37 SD and 0.20 SD, respectively. It is likely that Baseline 2 coincides with the period in which students are preparing for second mid-terms, as the semester usually ends in late May. A similar explanation could apply to the post-graduation period, which covers both a high-stress period—as the semester usually starts in August and is over by the end of November—and a lower stress period, when students are finished with their academic duties.

While the trends in these psychological measures for final-semester students largely follow those of the comparison group, suggesting a similar seasonality, there are interesting dynamics that become clearer when separating the two post-graduation periods (see Appendix Figure 6). We sometimes observe significantly higher levels of negative emotions for comparison students in the interim periods Baseline 2 and Post-graduation 1. However, their stress levels fall by Post-graduation 2, which is during vacation time. Therefore, our DID analysis pooling the last two stages (Table 9) may cancel out large seasonality effects, as we would be pooling periods with higher stress (midway through the semester) and lower stress (end of year vacation).

[22] Specifically, these measures ask about how frustrated, depressed, and worried the subject felt the previous day on a scale from 1 to 5, where 1 means the subject did not experience the feeling, and 5 that the feeling was an important part of the experience. For details, see the online appendix 2.6.

However, we cannot disentangle the following three explanations: (a) that both groups face similarly stressful circumstances and final-semester students cope better because of increased liquidity, (b) that both groups face entirely different circumstances with a coincidental seasonality, or (c) that the effects we pick up may simply be a product of final-semester students not worrying as much about exams in their last term because they matter less for jobs. If coping mechanisms matter, this would be consistent with findings from the literature showing that cash transfers reduce distress and depression (Haushofer & Fehr, 2014). We do observe that there are no significant differences in the index between final-semester and comparison students in the final survey, which is conducted during the vacation time, after graduation, when neither group has exams. This result may indicate that the differences observed in the index in previous periods arise simply because comparison students experience exam- and course-work-related stress more acutely. These effects are not visible when pooling the Post-graduation 1 and 2 periods, and therefore, may not be indicative of very large or sustained differences.

5 Robustness Checks

5.1 Multiple Hypothesis Testing

In the results tables, we use a dagger symbol (†) to denote the q-values that adjust the original p-values for the FDR (Benjamini & Yekutieli, 2005). We do so for each class of outcomes for which we collected multiple measures. The intuition is that we control for Type I errors by adjusting the original p-values for which we found false positives in 5% of all tests conducted, with q-values, which will find 5% of the significant results to be false positives.

These results corroborate most of the results that we discuss in Section 4 concerning the perception of liquidity and paying for one's own expenses. However, we do not find statistical significance using this testing method for our result on prosociality.

5.2 Selection Issues in the Student Sample

Although 95% of the students in our sample are pursuing engineering degrees, 5% are from other disciplines. We add an indicator variable for majoring in engineering as a control variable in all regression results so far. To ensure further that major choice does not affect our results, column 3 of Table 10 shows the DID estimates for each of our outcomes after excluding students in non-engineering majors. The table shows that the results are robust to this sample selection. Therefore, to maximize statistical power, we include our full sample (both engineering and non-engineering students) in our main analysis and control for whether students major in engineering.

Another possible selection consideration is that while some comparison students hold part-time jobs, others do not work at all. A possible robustness check to test the validity of our results is to generate the DID estimates comparing final-semester students with the subset of comparison students who do not work. Column 4 in Table 10 presents these results. Interestingly, we find a larger magnitude for the outcome variable measuring financial responsibilities (subjects pay for their own expenses), but we do not obtain a statistically significant effect for perception of liquidity (students reporting that it is hard to come up with money for an emergency), even though the coefficient is similar in magnitude to the main estimate. As many final-semester students were already working while in college, this restriction makes the comparison group less similar to the final-semester group. In addition, we lose about 65% of the comparison students with this sample restriction, which may reduce the statistical power. One explanation for the result is that the restricted sample of comparison students only includes those who received financial assistance from the university; hence, they perceive liquidity, but do not pay for their own expenses. We find their average tuition level (proportional to their financial status) to be lower than the full sample median. Such students usually receive free meals from the university, among other benefits.

5.3 The Role of Memory in Performance on Experimental Tasks

One potential concern about interpreting the changes (or lack thereof) in task performance between surveys is that students may remember their answers from the previous surveys. For instance, Baseline 1 and 2 are less than 30 days apart. As we needed to ensure that we captured the period before final-semester students began receiving job offers, we kept Baseline 2 close to Baseline 1, but still far enough apart to test reasonably for parallel trends. We carefully altered the values involved in the tasks to prevent students from completing tasks from memory. In addition, we varied the order in which students would see the tasks by randomizing them at the student and survey levels. We cannot completely eliminate the possibility that there may be a greater consistency in answers because of the short 30-day window between Baselines 1 and 2, but these measures mitigate such concerns.

However, consistent behavior across surveys is not necessarily correlated with length between surveys, as demonstrated by Figure 7. The plot shows the mean of correct answers in the Raven's test by group and across surveys. This test is particularly useful in assessing the role of memory, as the same test was administered in Baseline 1 and Post-graduation 1. Similarly, a second test, different from the one administered in Baseline 1 and Post-graduation 1, was administered in Baseline 2 and Post-graduation 2. There was no overlap in test questions between Baselines 1 and 2, which were 30 days apart, so memory would not play a role. Therefore, any changes from Baseline 1 to Baseline 2 could be related to familiarity with this type of task, the difficulty of the test, or the transition itself. Performance in tests at Baseline 1 and Post-graduation 1, and Baseline 2 and Post-graduation 2 can on the other hand, potentially demonstrate the role of memory. Figure 7 demonstrates an average of one additional correct answer when administering the same test from Baseline 1 to Post-graduation 1. We do not observe any increase in correct answers from Baseline 2 to Post-graduation 2, which also had the same test questions. If memory had played an important role in how students answered our tasks, we would expect to see larger increases in correct answers in the repeat test questions.

5.4 Attrition

In this section, we assess how students who leave the sample differ from those who stay in terms of observable characteristics. As in any longitudinal study, some attrition is to be expected. In our case, it amounts to 18.6% of the sample from baseline to post-graduation. We provide evidence that it is unlikely that selection into staying in the sample drives the results presented in section 4.

First, we examine how baseline characteristics among stayers and leavers vary in Table 12. About 45% of those who are in the sample at baseline are final-semester students. However, the probability of losing a final-semester student from the sample is higher post-graduation. Furthermore, more men leave the sample after baseline. Other baseline characteristics do not differ significantly between leavers and stayers. In Table 13, we examine whether outcomes measured at baseline are related to staying in the sample. Similar to Table 12, we compare the means of the outcomes at baseline between stayers and leavers. We do not see any meaningful differences, except that students who left the sample gave 6 pp more to the NGO relative to those who stayed.

We do not find it surprising that more final-semester students leave the sample given that they eventually graduate and find jobs. They either do not check their university e-mail as often (because they are no longer students), do not have the time to participate, or do not need the cash incentive. It is reassuring that even though final-semester students are more likely to disappear from the sample, we do not find substantial differences in baseline outcomes. Importantly, as noted above, those who left were slightly more likely to donate more to the NGO, so they cannot explain the results relating to this variable.

6 Conclusion

This paper examines changes in behavior and decision-making over the course of a universal yet understudied transition: progressing from college to the labor force. We collect a wide array of measures across a period of 8 months from students who graduate from a large public university in Colombia, as well as from a comparison group of students who are yet to go through this transition. Our context is unique in the sense that we have a convenient sample (as in standard lab experiments) that we can observe and follow as they undergo real and important changes in their life cycle. Furthermore, it allows us to observe how individuals who become richer as a result of obtaining a full-time job behave in our experimental tasks. We provide ITT as well as IPW estimates from a DID design to understand the changes (or lack thereof) in various outcomes, including emotional measures, cognitive performance, and economic and social preferences.

We find that after leaving college and starting a new job, the number of students who report hardship in raising money for an emergency is significantly reduced, demonstrating an increase in perceived liquidity. In addition, students report taking on increased responsibilities, even though their levels of credit take-up or independence from their parents do not increase. We provide suggestive evidence of a lower degree of present-biased behavior and higher giving (prosociality) to NGOs as a result of going through the college-to-labor-market transition. However, we do not find any differential changes in experimental measures of risk or ambiguity preferences, or performance in cognitive tasks between students going through the transition and students in the comparison group.

These results may be contextualized in the environment described in the conceptual framework. The results are consistent with a mix of individuals, some of whom have accurate expectations about the transition, although a majority have inaccurate expectations about the transition and their future income. In the presence of credit constraints, as in our setting, such individuals would be expected to perceive greater liquidity and take care of their own expenses when their incomes increase. In addition, donations, being a normal good, would be expected to increase. Similarly, they may be expected to appear more patient and forward looking, i.e., have a lower marginal rate of intertemporal substitution (Dean & Sautmann, 2021), as their income increases. Nevertheless, a large percentage of our sample overestimates their future incomes and, consequently, face a lower-than-expected income increase, which may counteract some of the effects associated with an income increase. This may explain why we do not see changes in risk preferences or cognitive performance.

This framework further predicts a fall in negative emotions such as stress. However, empirically, we are unable to provide evidence of differential changes in the post-graduation period, as we are pooling together periods with potentially high and low stress levels. We observe that comparison students face a larger amount of seasonality in their negative emotions. Therefore, although we cannot rule out that final-semester students cope with stress better because of higher incomes and lower uncertainty, we cannot assert this in an unqualified manner. It may be that final-semester students experience the same seasonality in emotions, but to a slightly more muted level, as they do not have to contend with exams and assignments after graduation.

Our results are among the first to describe an understudied but common phenomenon around the world: graduating from college and starting a full-time job. This not only represents a structural and permanent increase in future income, but also provides a context where this happens organically, rather than being experimentally induced. Furthermore, this income increase is a result of effort exerted by the subjects and not externally provided. This paper provides a framework and empirical results describing the dynamics that occur during this transition. These may be able to feed into policy-making, especially policies influencing long-term decisions that are made around the time of this transition, such as choices of health-care and pension plans, and may be helpful in designing policies intended to motivate people to donate.

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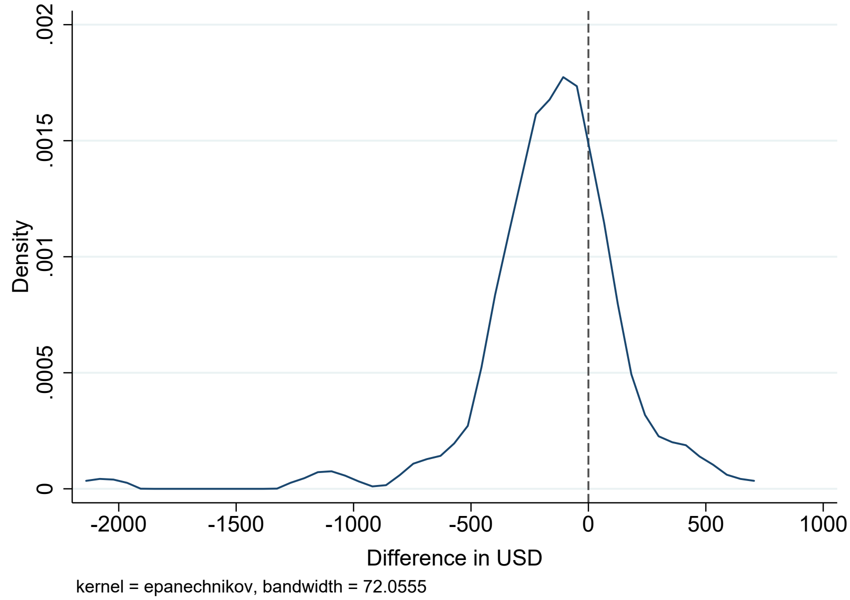
Figures

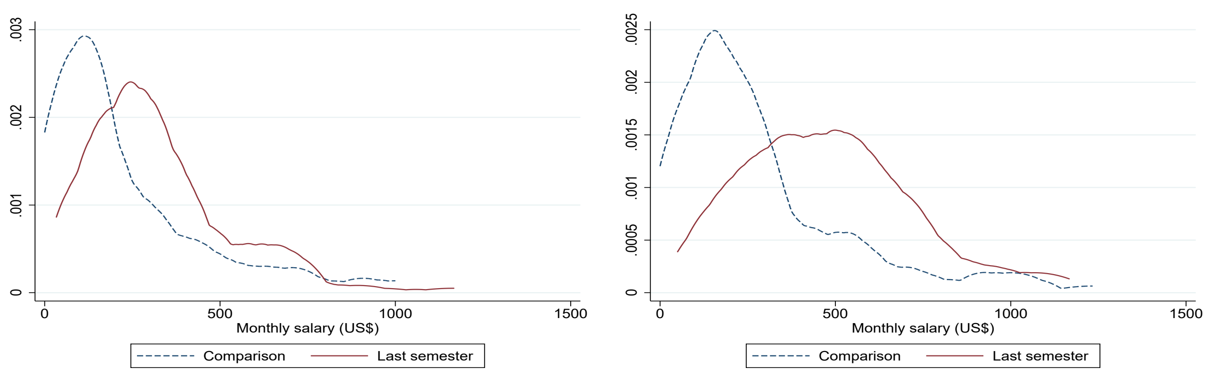
Figure 1: Difference between realized and expected salary



Notes: The graph plots the difference between the reported actual salary post-graduation and the expected salary reported at sign-up for final-semester students. The difference is calculated by subtracting expected salary from actual salary, using 108 observations, or the 60% of all final-semester students who reported data on salaries.

Figure 2: Densities of salaries

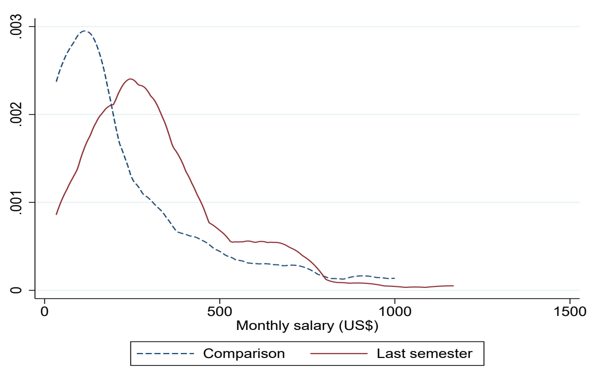
(a) Baseline (b) Post-graduation



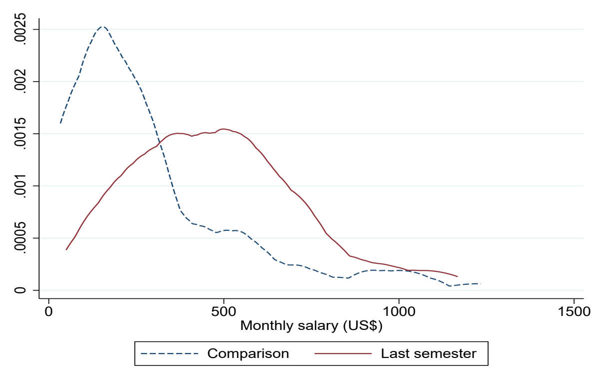
Notes: The figure shows salaries of students working in full- or part-time jobs who report a salary. Students with no reported salary are assigned a salary equal to zero. Salaries are converted into US dollars using the exchange rate of 3,000 COP for 1 USD. Salaries in the top percentile (1 student at baseline and 1 after graduation) were excluded to account for outliers.

Figure 3: Densities of salaries (only nonzero salaries)

(a) Baseline



(b) Post-graduation



Notes: This figure shows salaries of students working in full-time or part-time jobs who report a salary. Students with no reported salary are excluded. Salaries are converted to US dollars using the exchange rate of 3,000 COP for 1 USD. Salaries in the top percentile (1 student at baseline and 1 after graduation) were excluded to account for outliers.

Tables

Table 1: Summary of research design and academic calendar

	Pre-graduation				Post-graduation		
Final-semester students	Send resumes Job interviews				Receive and accept a job offer Start a new job / continue in previous job Receive a paycheck		
Comparison students				Normal student life			
Survey administration	April 19-29 Baseline 1	May 5-18 Baseline 2				Sept. 25 - Nov. 1 Post-grad 1	December 8-26 Post-grad 2
Academic calendar	**Semester I, 2016**		**Break**		**Semester II, 2016**		**Break**
Feb. 1 Classes start		May 28 Classes end	June and July	August 1 Classes start	August 15-26 Graduation ceremony	Nov. 26 Classes end	December and January

Notes: Final-semester students are in their final semester in college. Comparison students are in lower years and selected to match final-semester students in gender, major, and economic background. This table describes the timeline for the three stages in this study: Stage 1 refers to two surveys conducted, Baselines 1 and 2. We had planned that Post-graduation 1 (Post-graduation 2) would be administered when most final-semester students had received job offers (started full-time jobs and receive paychecks). In practice, however, the timing of these stages was challenging, and we pooled Post-graduation 1 and 2 in the main analysis. Final exams usually take place during the last week of classes, as final grades must be uploaded in the system about 5 days after classes end. The full 2016 academic calendar can be found at: http://www.legal.unal.edu.co/rlunal/home/doc.jsp?d_i=86052

Table 2: Differences in baseline characteristics

Variable	(1) Comparison	(2) Last semester	(3) Difference
Female	0.26	0.25	-0.01
	(0.44)	(0.43)	(0.79)
Age	22.96	25.07	2.11***
	(3.81)	(2.91)	(0.00)
Undergraduate student	0.87	0.88	0.01
	(0.34)	(0.32)	(0.73)
Semester in college	6.20	10.41	4.21***
	(3.05)	(2.48)	(0.00)
GPA	3.80	3.81	0.01
	(0.37)	(0.33)	(0.75)
Residential stratum (1=lowest, 6=highest)	2.84	2.93	0.10
	(0.88)	(0.79)	(0.28)
Fraction with tuition below median (US$200)	0.54	0.59	0.05
	(0.50)	(0.49)	(0.35)
Poor	0.37	0.38	0.01
	(0.48)	(0.49)	(0.78)
Not in engineering college	0.06	0.05	-0.01
	(0.24)	(0.22)	(0.71)
No. semesters working full time	0.32	0.52	0.20*
	(1.00)	(1.06)	(0.07)
No. semesters working part time	1.97	2.84	0.87***
	(1.85)	(1.93)	(0.00)
No. semesters in internship	0.09	0.53	0.44***
	(0.34)	(0.77)	(0.00)
Expected monthly first salary after college (USD)	684.50	652.61	-31.89
	(281.22)	(297.12)	(0.29)
Observations	186	179	365

Notes: Final-semester students are in their final semester in college. Comparison students are in lower years and were selected to match final-semester students in gender, major, and economic background. We do not have information on these characteristics for the period in which final-semester students were in the same semester as comparison students, so all comparisons reflect students at different stages of their college progression. Although we report p-values of the differences in means at baseline in this table, it should be noted that our empirical strategy does not require equality of level means, but rather parallel trends, which we show in the results tables. Statistical significance of the differences is denoted by *** p<0.01, **p<0.05, and * p<0.1.

Table 3: Job status and salaries by stage

	Baseline: Apr., 2016		Post-graduation 1: Oct., 2016		Post-graduation 2: Dec., 2016	
	Comparison	Final-semester	Comparison	Final-semester	Comparison	Final-semester
Total sample	183	177	160	140	155	127
Not working	100	59	84	45	79	38
	54.6 %	33.3 %	52.5 %	32.1 %	51.0 %	29.9 %
Working	83	118	76	95	76	89
	45.4 %	66.7 %	47.5 %	67.9 %	49.0 %	70.1 %
Type of job:						
Full-time	21.7 %	28.8 %	25.0 %	60.0 %	30.3 %	75.3 %
Part-time	75.9 %	47.5 %	61.8 %	30.5 %	61.8 %	19.1 %
Internship	2.4 %	23.7 %	13.2 %	9.5 %	7.9 %	5.6 %
Job relates to major	44.6 %	78.8 %	55.3 %	74.7 %	53.9 %	79.8 %
Salaries (assigning 0 to those not working):						
Mean	326,290	616,287	381,625	879,706	412,323	1,059,057
SD	664,491	677,826	687,754	852,848	681,904	932,367
Min	0	0	0	0	0	0
Max	4,800,000	3,500,000	3,700,000	3,400,000	3,700,000	3,860,000
N	174	167	148	133	145	122

Notes: Final-semester students are in their final semester in college. Comparison students are in lower years and selected to match final-semester students in cells containing gender, major, and economic background. The minimum wage in 2016 was 689,454 COP. The exchange rate for the period is about 3,000 COP for 1 USD.

Table 4: Changes in perceived liquidity and credit take-up

	Liquidity constraints		Credit takeup	
	(1)	(2)	(3)	(4)
	ITT	IPW	ITT	IPW
Baseline 2	0.065**			
	(0.033)			
Post	0.038		0.038	
	(0.035)		(0.031)	
Last-sem.	-0.008		0.064	
	(0.062)		(0.067)	
Baseline 2 × Last-sem.	-0.062			
	(0.047)			
Post × Last-sem.	-0.143***††	-0.153***†††	0.029	0.049
	(0.052)	(0.049)	(0.050)	(0.058)
Constant	1.829***		-0.807**	
	(0.306)		(0.406)	
Mean comparison baseline	0.59	0.63	0.35	0.39
Observations	1,346	317	950	303
No. students	365		363	

Notes: Columns 1 and 3 show the coefficients of a DID regression of the outcomes in the top row on the variables on the left. The coefficients on the interaction term with Baseline 2 assess the validity of parallel pre-trends, and those with Post demonstrates the DID effect of being a final-semester student compared with the comparison group. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. The credit variable was not collected in Baseline 1, so the constant refers to the level in Baseline 2. Standard errors are clustered at the student level. The symbols ***, **, and * denote that p<0.01, p<0.05, and p<0.1, respectively. Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Table 5: Changes in independence and responsibilities

	Resposibilities		Independence	
	(1)	(2)	(3)	(4)
	ITT	IPW	ITT	IPW
Baseline 2	-0.000			
	(0.000)			
Post	0.090***		-0.001	
	(0.029)		(0.012)	
Last-sem.	0.137***		0.018	
	(0.053)		(0.030)	
Baseline 2 × Last-sem.	0.000			
	(0.000)			
Post × Last-sem.	0.084*†	0.109**††	0.013	0.027
	(0.046)	(0.053)	(0.022)	(0.027)
Constant	-0.228		-0.219	
	(0.334)		(0.223)	
Mean comparison baseline	0.21	0.30	0.05	0.04
Observations	1,313	303	950	303
No. students	363		363	

Notes: Columns 1 and 3 show the coefficients of a DID regression of the outcomes in the top row on the variables on the left. The coefficients on the interaction term with Baseline 2 assess the validity of parallel pre-trends, and those with Post demonstrate the DID effect of being a final-semester student compared with the comparison group. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. The responsibilities and independence variables were not collected in Baseline 1, so the constant refers to the level in Baseline 2. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively. The Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Table 6: Risk and ambiguity preferences

	Risk aversion: CRRA		Ambiguous choices (out of 9)	
	(1)	(2)	(3)	(4)
	ITT	IPW	ITT	IPW
Baseline 2	0.075		-0.011	
	(0.117)		(0.152)	
Post	-0.450***		0.563***	
	(0.124)		(0.160)	
Last-sem.	0.277		-0.074	
	(0.185)		(0.273)	
Baseline 2 × Last-sem.	-0.117		-0.125	
	(0.170)		(0.248)	
Post × Last-sem.	0.005	0.184	-0.189	-0.098
	(0.180)	(0.162)	(0.240)	(0.221)
Constant	1.322		2.691*	
	(1.032)		(1.420)	
Mean comparison baseline	1.12	0.71	3.77	4.21
Observations	1,318	306	1,322	309
No. students	365		365	

Notes: Columns 1 and 3 show the coefficients of a DID regression of the outcomes in the top row on the variables on the left. The coefficients on the interaction term with Baseline 2 assess the validity of parallel pre-trends, and those with Post demonstrate the DID effect of being a final-semester student compared with the comparison group. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively. The Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Table 7: Intertemporal choices

	Amount to sooner period all students		Amount to sooner period cond. on understanding	
	(1) ITT	(2) IPW	(3) ITT	(4) IPW
Soon: reward in 1 week	-0.80***		-0.67***	
	(0.17)		(0.25)	
Interest rate	-2.18***		-2.76***	
	(0.19)		(0.25)	
Delay: 8 weeks	1.22***		1.43***	
	(0.23)		(0.33)	
Post	2.67***		2.94***	
	(0.62)		(0.87)	
Last-sem.	0.34		1.25	
	(0.93)		(1.16)	
Post × Last-sem.	-0.13	-1.01***†††	-1.41	-0.66**††
	(0.95)	(0.23)	(1.28)	(0.28)
Post × Last-sem. × Soon	-0.14	-0.05	-0.31	0.00
	(0.32)	(0.16)	(0.40)	(0.19)
Post × Last-sem. × Int. rate	0.10	0.37***†††	0.63	0.32***†††
	(0.28)	(0.07)	(0.39)	(0.08)
Post × Last-sem. × Delay	-0.10	0.06	-0.40	-0.20
	(0.25)	(0.16)	(0.34)	(0.19)
Constant	9.46***		11.64**	
	(3.58)		(5.04)	
Mean comparison baseline	6.20	6.17	6.45	6.62
Choices	20,992	19,648	13,360	12,144
No. students	365		318	

Notes: Columns 1 and 3 show the coefficients of a fully saturated DID regression of the amount allocated to the sooner period out of the endowment of 50,000 COP. The trade-offs between a sooner or later payment involve: 1 week vs. 5 weeks, 1 week vs. 9 weeks, 5 weeks vs. 9 weeks, and 5 weeks vs. 13 weeks. The Soon variable equals one if the trade-off involves a payment 1 week from today. The Delay variable indicates whether the trade-off concerns 8 weeks of separation between the sooner and later payments. The Interest rate variable contains four categories for each interest rate earned for delaying payment: 1%, 10%, 50%, and 100%. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively. The Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Table 8: Prosociality

	Fraction donated to participant		Fraction donated to NGO	
	(1)	(2)	(3)	(4)
	ITT	IPW	ITT	IPW
Baseline 2	-0.049***		-0.080***	
	(0.016)		(0.017)	
Post	-0.099***		-0.176***	
	(0.020)		(0.025)	
Last-sem.	0.052		0.002	
	(0.032)		(0.048)	
Baseline 2 × Last-sem.	0.021		0.020	
	(0.025)		(0.025)	
Post × Last-sem.	-0.012	0.014	0.040	0.054*
	(0.030)	(0.029)	(0.035)	(0.032)
Constant	0.536**		0.479*	
	(0.213)		(0.246)	
Mean comparison baseline	0.33	0.24	0.55	0.38
Observations	1,312	303	1,309	303
No. students	365		365	

Notes: Columns 1 and 3 show the coefficients of a DID regression of the outcomes in the top row on the variables on the left. The coefficients on the interaction term with Baseline 2 assess the validity of parallel pre-trends, and those with Post demonstrate the DID effect of being a final-semester student compared with the comparison group. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively. The Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Table 9: Psychological and cognitive measures

	Index negative emotions		Index cognitive measures	
	(1)	(2)	(3)	(4)
	ITT	IPW	ITT	IPW
Baseline 2	0.390***		0.573***	
	(0.063)		(0.051)	
Post	0.190**		0.532***	
	(0.076)		(0.053)	
Last-sem.	-0.086		-0.114	
	(0.112)		(0.088)	
Baseline 2 × Last-sem.	-0.137		0.056	
	(0.095)		(0.072)	
Post × Last-sem.	-0.034	0.031	0.030	-0.004
	(0.109)	(0.105)	(0.075)	(0.068)
Constant	0.626		-1.589***	
	(0.660)		(0.486)	
Mean comparison baseline	-0.39	-0.04	-0.58	-0.27
Observations	1,311	303	1,345	316
No. students	365		365	

Notes: Columns 1 and 3 show the coefficients of a DID regression of the outcomes in the top row on the variables on the left. The index of negative emotions includes stress, frustration, depression, and worry. The index of cognitive measures includes performance in the Raven's test, CRT, Flanker test, and numerical Stroop test. The coefficients on the interaction term with Baseline 2 assess the validity of parallel pre-trends, and those with Post demonstrate the DID effect of being a final-semester student compared with the comparison group. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively. The Q-values adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Table 10: Main estimates and robustness

	(1) Base model	(2) IPW	(3) Engineering	(4) Non-workers
Liquidity constraints	-0.143***	-0.153***	-0.143***	-0.102
	(0.052)	(0.049)	(0.052)	(0.072)
Credit takeup	0.029	0.049	0.028	0.038
	(0.049)	(0.058)	(0.049)	(0.058)
Responsibilities	0.084*	0.109**	0.084*	0.127***
	(0.046)	(0.053)	(0.046)	(0.045)
Independence	0.013	0.027	0.012	0.030
	(0.022)	(0.027)	(0.022)	(0.024)
CRRA	0.005	0.184	-0.007	0.071
	(0.180)	(0.162)	(0.180)	(0.224)
Ambiguous choices	-0.189	-0.098	-0.188	-0.572*
	(0.240)	(0.221)	(0.240)	(0.334)
Fraction donated to other participant	-0.012	0.014	-0.012	-0.034
	(0.030)	(0.029)	(0.030)	(0.038)
Fraction donated to NGO	0.040	0.054*	0.038	0.046
	(0.035)	(0.032)	(0.035)	(0.042)
Index negative emotions	-0.034	0.031	-0.020	0.137
	(0.109)	(0.105)	(0.109)	(0.148)
Index cognitive measures	0.030	-0.004	0.020	-0.031
	(0.075)	(0.068)	(0.075)	(0.099)

Notes: Each column shows the coefficients of a DID regression of the outcomes in the top row on the variables on the left. All regressions control for baseline covariates and include stratification cells fixed effects. The Baseline 1 coefficient shows the mean of the outcome for comparison students in the first data collection. The coefficients on the interaction term with Baseline 2 assess the validity of parallel pre-trends, and those with Post demonstrates the DID effect of being a final-semester student compared with a comparison student. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Column 2 reports the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Column 3 presents DID estimates using a subset of comparison students who do not work. Column 4 presents DID estimates using a subset of students who are pursuing an engineering major. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively. The Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1. Standard errors are clustered at the student level. The symbols ***, **, and * denote that p<0.01, p<0.05, and p<0.1, respectively.

Table 11: Main estimates and robustness: Intertemporal choices

	(1) ITT	(2) IPW	(3) Non-workers	(4) Engineering
Soon: reward in 1 week	-0.80***		-0.81***	-0.66**
	(0.17)		(0.18)	(0.30)
Interest rate	-2.18***		-2.19***	-2.06***
	(0.19)		(0.19)	(0.33)
Delay: 8 weeks	1.22***		1.22***	1.18***
	(0.23)		(0.23)	(0.33)
Post	2.67***		2.64***	2.58***
	(0.62)		(0.62)	(0.91)
Last-sem.	0.34		0.33	1.67
	(0.93)		(0.93)	(1.35)
Post × Last-sem.	-0.13	-1.01***	-0.09	-0.03
	(0.95)	(0.23)	(0.95)	(1.16)
Post × Last-sem. × Soon	-0.14	-0.05	-0.14	0.26
	(0.32)	(0.16)	(0.32)	(0.44)
Post × Last-sem. × Int. rate	0.10	0.37***	0.09	-0.11
	(0.28)	(0.07)	(0.28)	(0.36)
Post × Last-sem. × Delay	-0.10	0.06	-0.09	-0.19
	(0.25)	(0.16)	(0.25)	(0.35)
Constant	9.46***		9.47***	17.08***
	(3.58)		(3.59)	(4.75)
Mean comparison baseline	6.20	6.17	6.23	6.12
Choices	20,992	19,648	20,912	13,744
No. students	365		363	245

Notes: Columns 1, 3, and 4 show the coefficients of a fully saturated DID regression of the amount allocated to the sooner period out of the endowment of 50,000 COP. The trade-offs between a sooner or later payment involve: 1 week vs. 5 weeks, 1 week vs. 9 weeks, 5 weeks vs. 9 weeks, and 5 weeks vs. 13 weeks. The Soon variable equals one if the trade-off involves a payment 1 week from today. The Delay variable indicates whether the trade-off concerns 8 weeks of separation between the sooner and the later payment. The Interest rate variable contains four categories for each interest rate earned for delaying payment: 1%, 10%, 50%, and 100%. The DID regressions include controls for gender, age, undergraduate status, engineering program, semester in college, GPA, socioeconomic status, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Columns 2 and 4 report the DID coefficient obtained through the IPW method in Abadie (2005). The propensity score includes the following predictors: gender, engineering program, GPA, socioeconomic background, tuition bin, number of semesters employed at baseline, and expected first salary after graduation. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that $p<0.01$, $p<0.05$, and $p<0.1$, respectively. The Q-values are adjusted for the FDR: †††<0.01, ††<0.05, and †<0.1.

Appendix

Previous Research Design

Our aim was to target three main stages of the transition from college to the labor force: job search, accepting a job offer, and receiving the first paycheck. We collect our outcomes of interest through online surveys twice at baseline (April 2016), when final-semester and comparison group students are all in college, and in October (Post-graduation 1) and December (Post-graduation 2), when final-semester students have graduated and, most likely, have a job offer and have started receiving paychecks if they have started the job. In practice, distinguishing between Post-graduation 1 and Post-graduation 2 proved difficult because of variations in the timing at which students received offers and commenced their jobs. Therefore, we characterize the transition as having baseline measures (from the two baseline surveys) and post-graduation measures (Post-graduation 1 and 2), presenting our reduced form results as pooled estimates from Post-graduation 1 and 2. We discipline the expectations for each outcome within the framework of a conceptual outline.

Attrition

Table 12: Tests for sample attrition (baseline characteristics)

Variable	(1) In sample	(2) Not in sample	(3) Difference
Last semester students	0.45	0.68	0.23***
	(0.50)	(0.47)	(0.00)
Female	0.27	0.16	-0.11**
	(0.45)	(0.37)	(0.03)
Age	23.97	24.19	0.22
	(3.74)	(2.49)	(0.56)
Undergraduate student	0.88	0.87	-0.01
	(0.33)	(0.34)	(0.81)
Semester in college	8.14	8.81	0.67
	(3.48)	(3.53)	(0.16)
GPA	3.80	3.83	0.02
	(0.35)	(0.35)	(0.64)
Residential stratum (1=lowest, 6=highest)	2.89	2.85	-0.04
	(0.83)	(0.87)	(0.74)
Fraction with tuition below median (US$200)	0.56	0.57	0.01
	(0.50)	(0.50)	(0.83)
Poor	0.38	0.32	-0.06
	(0.49)	(0.47)	(0.34)
Not in engineering college	0.05	0.07	0.02
	(0.22)	(0.26)	(0.49)
No. semesters working full time	0.42	0.41	-0.01
	(1.06)	(0.88)	(0.95)
No. semesters working part time	2.36	2.58	0.22
	(1.96)	(1.85)	(0.40)
No. semesters in internship	0.28	0.45	0.18
	(0.57)	(0.84)	(0.10)
Expected monthly first salary after college (USD)	676.26	636.52	-39.74
	(288.44)	(292.32)	(0.31)
Observations	297	68	365

Notes: Means and standard errors for each variable are on the left-hand side for students who remain in the sample in the post-graduation period and those who do not. Final-semester students are in their final semester in college. Comparison students are in lower years and selected to match final-semester students in gender, major, and economic background. Standard errors are clustered at the student level. The symbols ***, **, and * indicate that p<0.01, p<0.05, and p<0.1, respectively.

Table 13: Tests for sample attrition (outcomes at baseline)

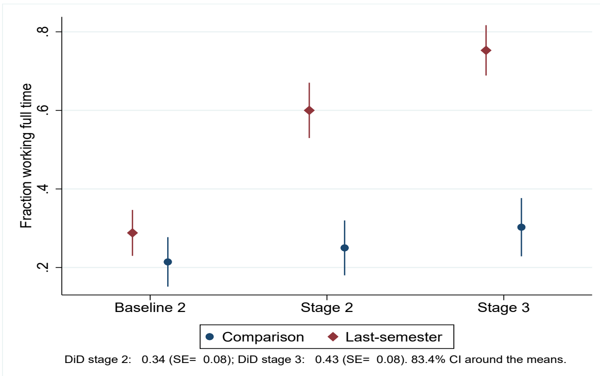
Variable	(1) In sample	(2) Not in sample	(3) Difference
Liquidity constraints	0.56	0.59	0.03
	(0.50)	(0.50)	(0.66)
Credit takeup	0.39	0.48	0.09
	(0.49)	(0.50)	(0.17)
Responsibilities	0.30	0.30	0.01
	(0.46)	(0.46)	(0.91)
Independence	0.07	0.03	-0.04
	(0.25)	(0.17)	(0.15)
CRRA	1.16	1.13	-0.03
	(1.36)	(1.34)	(0.87)
Ambiguous choices	3.82	3.99	0.17
	(1.97)	(1.72)	(0.48)
USD allocated to sooner period (decision 4)	2.81	2.30	-0.51
	(3.96)	(3.85)	(0.33)
USD allocated to sooner period (decision 8)	3.12	2.79	-0.33
	(3.73)	(4.06)	(0.54)
USD allocated to sooner period (decision 12)	3.27	3.22	-0.06
	(4.10)	(4.24)	(0.92)
USD allocated to sooner period (decision 16)	4.05	5.09	1.04
	(4.78)	(5.73)	(0.16)
Fraction donated to other participant	0.33	0.39	0.06*
	(0.24)	(0.23)	(0.06)
Fraction donated to NGO	0.53	0.55	0.03
	(0.32)	(0.32)	(0.55)
Index negative emotions	-0.43	-0.43	-0.01
	(0.83)	(0.86)	(0.94)
Index cognitive measures	-0.59	-0.65	-0.07
	(0.67)	(0.72)	(0.48)
Observations	297	68	365

Notes: Means and standard errors for each variable are on the left-hand side for students who remain in the sample in the post-graduation period and those who do not. For the intertemporal choices task, we report four of the 16 choices owing to space considerations. The choices that we report present the trade-offs with the biggest interest rate (100%) in the later period. The symbols ***, **, and * indicate that $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

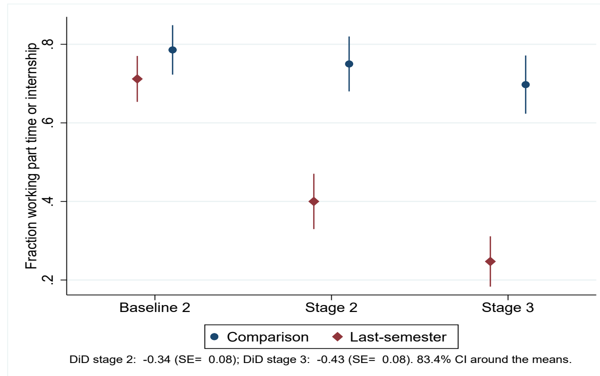
Additional Figures

Figure 4: Flows from part-time to full-time work

(a) Full-time work



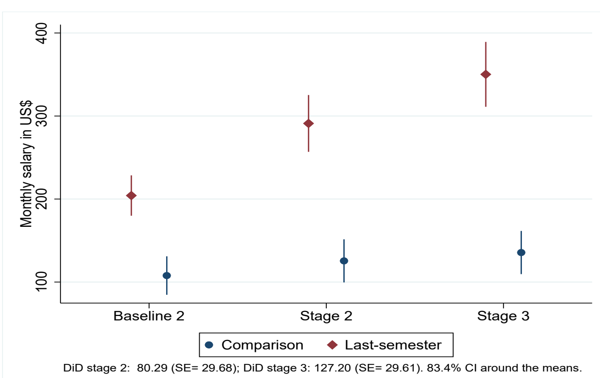
(b) Part-time work and internships



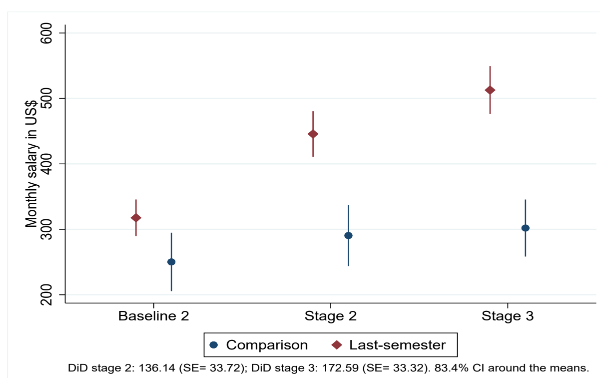
Notes: The sample includes participants who reported working at each stage: 202 in Baseline 2, 171 in Post-graduation 1, and 165 in Post-graduation 2. The corresponding numbers of students who report not working are: 161 in Baseline 2, 132 in Post-graduation 1, and 120 in Post-graduation 2. Students who are not working are not included in the plot. We use 83.4% confidence intervals as they have been found to provide a visual way of showing when two coefficients are statistically different from each other (Tryon & Lewis, 2008). In this example, nonoverlapping confidence intervals can be interpreted to mean that the estimates for final-semester and comparison students are statistically different from each other.

Figure 5: Mean salaries by group

(a) Mean salaries including zeros

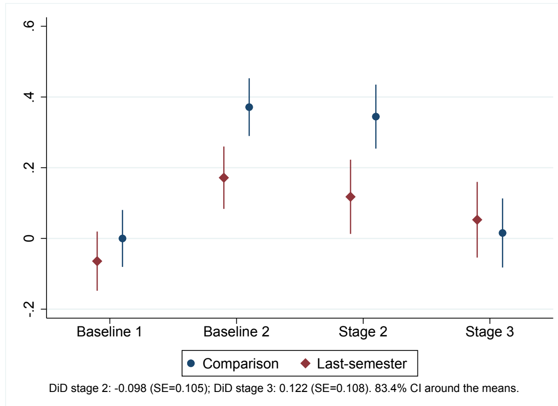


(b) Mean salaries not including zeros

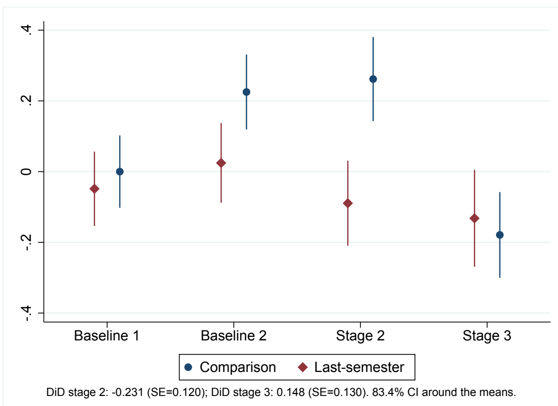


Notes: The graph plots the mean reported salaries by comparison and final-semester students at each stage in which students responded to our survey. Salaries are converted to US dollars using the exchange rate of 3,000 COP for 1 USD. Salary information was not collected in Baseline 1. We use 83.4% confidence intervals as they have been found to provide a visual way of showing when two coefficients are statistically different from each other (Tryon & Lewis, 2008). In this example, nonoverlapping confidence intervals can be interpreted to mean that the estimates for final-semester and comparison students are statistically different from each other.

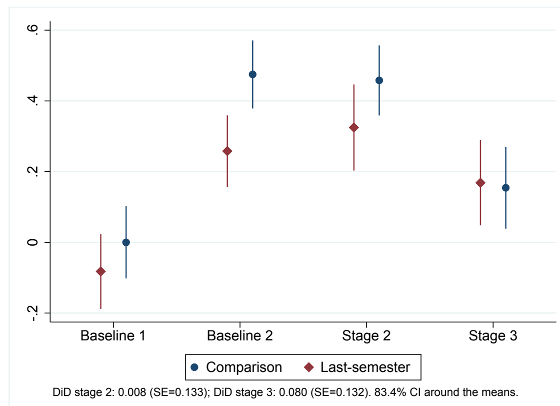
Figure 6: Psychological measures



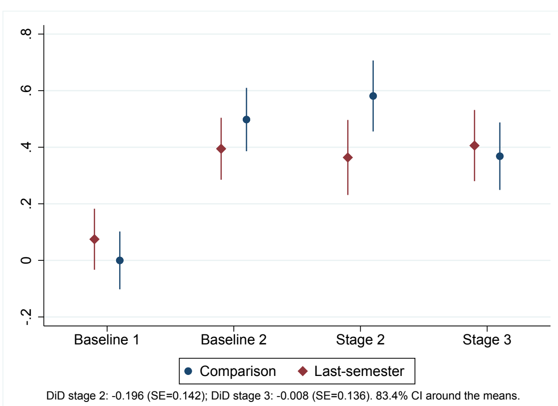
(a) Index of negative emotions



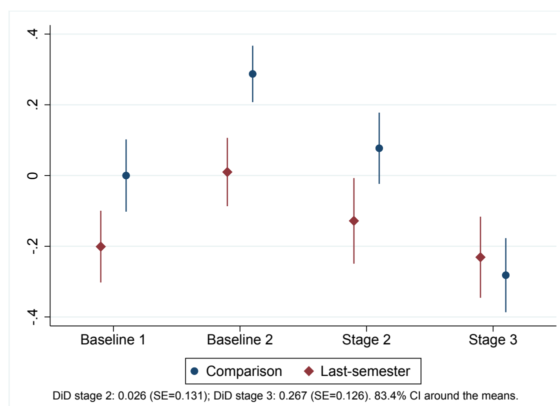
(b) Perceived Stress Scale (standardized)



(c) Frustrated (standardized)



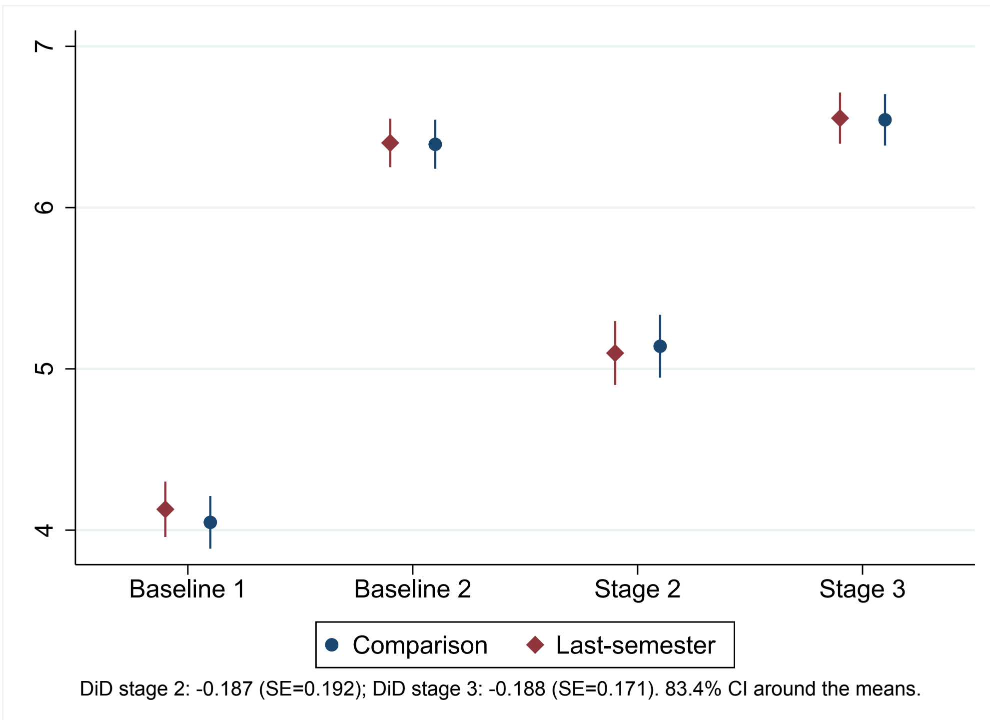
(d) Depressed (standardized)



(e) Worried (standardized)

Notes: The graphs plot the mean values for various standardized emotional measures by comparison and final-semester students at each stage in which students responded to our survey. These values range between 0 and 1. We use standard measures, including Cohen's PSS (Cohen et al., 1994) and other self-reported measures of subjective well-being used in Carvalho et al. (2016). We use 83.4% confidence intervals as they have been found to provide a visual way of showing when two coefficients are statistically different from each other (Tryon & Lewis, 2008). In this example, nonoverlapping confidence intervals can be interpreted to mean that the estimates for final-semester and comparison students are statistically different from each other.

Figure 7: Performance in Raven's test



Notes: The graph plots the mean number of correct answers in the short version of the Raven's test, which includes a total of nine questions to be answered in 3 minutes. Two versions of the test were administered: one at Baseline 1 and Post-graduation 1, and the other one at Baseline 2 and Post-graduation 2. We use 83.4% confidence intervals as they have been found to provide a visual way of showing when two coefficients are statistically different from each other (Tryon & Lewis, 2008). In this example, nonoverlapping confidence intervals can be interpreted to mean that the estimates for final-semester and comparison students are statistically different from each other.