

Housing by chance: The impacts of lottery-based access to student accommodation*

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Abstract

The affordability and stability of housing are key determinants of economic well-being, but their effects on the academic success of university students remain underexplored. This paper investigates the causal effect of early access to affordable student housing on academic performance using a unique lottery-based allocation system in Sweden. The findings show that early access to student housing significantly improves students' academic performance, with grades increasing by 23% of a standard deviation, and students being 34% more likely to rank in the top 10% of their class. The results point to a 2 to 6 percentage point reduction in full-time employment, shorter commutes, and greater housing stability as plausible channels behind this effect.

Keywords: Student Housing, Higher Education, Test Scores

JEL Classification: I21 ,I23, R21, C93

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1 Introduction

Housing (un)affordability is a global problem with harmful consequences for the economy, including rising income and social inequality, limitations in labor mobility, and potential negative effects on economic growth (UN Habitat, 2015; Albouy et al., 2016; Glaeser and Gyourko, 2018; Hsieh and Moretti, 2019; Dustmann et al., 2022). Meanwhile, the demand for accommodation among university students is increasing as more students than ever attend university to pursue higher education. This has put pressure on housing markets as the current supply cannot meet the growing need for accommodation and has left students facing relatively higher rents (The Guardian, 2023). Experiencing housing insecurity, such as moving several times in a year, defaulting on rent or mortgage, short contracts, and sharing accommodation with others due to financial difficulties, personal support needs, convenience, or social and emotional reasons, is not uncommon among university students (Goldrick-Rab et al., 2017; Broton and Goldrick-Rab, 2018; Hallett and Freas, 2018; Broton et al., 2022; SFS, 2024).¹ This instability can negatively affect student performance and reduce the accumulation of human capital. Educational performance in university predicts later labor market success through several channels, including signaling, human capital accumulation, and sorting into more selective postgraduate opportunities. Therefore, the effects of housing instability can extend to employment, productivity, and lifetime earnings (Freier et al., 2015; Silva et al., 2017; Altonji and Zhong, 2021).

To help students find affordable accommodation, many universities offer various housing options, including dormitories both on- and off-campus, as well as facilitating access to affordable units through special agreements with partner housing companies. These accommodations typically feature two key advantages: they are usually more affordable than other options of similar size and location, and they are more accessible, as many admitted university students qualify to apply for them. Yet, almost no

¹In Sweden, which is the context of this paper, housing insecurity is a pressing issue for university students. Seventy percent of students live in cities that cannot offer them suitable accommodation during the fall semester (SFS, 2024). Furthermore, 1 in 4 students declines a university offer due to the lack of available housing at their place of study (Sveriges Radio, 2024). The severity of the crisis has led to a recent motion in the Swedish Parliament, calling for urgent reforms to student housing policies and increased investment in student housing units (Riksdagen, 2022). This paper studies the effect of a student housing lottery in Lund, one of the cities where student housing shortages are particularly problematic.

causal evidence exists on the effects of gaining access to student housing on the students' outcomes. A key challenge is that access to student housing and the timing of this access is often not randomly assigned but rather based on more or less explicit criteria. Simply comparing outcomes between students who live in student housing and those who either do not or move in later during the academic year fails to yield causal estimates, as they may systematically differ in terms of unobservable characteristics.

This paper evaluates the impact of early access to affordable student housing on educational achievement. To identify a causal effect, I exploit a student housing lottery in Sweden that effectively randomized the probability that a student gained access to affordable student accommodation at the beginning of the academic year. Using this lottery, I study how access to student housing and its timing affect academic outcomes for incoming students. Since the lottery rank is unrelated to the background characteristics of the students, this ensures that the variation in the time to receive accommodation is independent of other factors that may affect the students' educational outcomes.

The affordability of the housing units offered by this lottery and the stability of the subsequent housing arrangements may play an important role in influencing various aspects of the students' lives such as their well-being and performance at university. Early access to housing may reduce the stress and uncertainty of finding a place to live, which allows students to focus on their coursework from the beginning of the semester. It might also support better time management, so students can establish consistent routines and devote more attention to both academic and extracurricular activities. Moreover, early access to housing, or the lack thereof, could affect students' decisions to work while studying, which in turn shapes their time allocation and consumption behavior.² I hypothesize that access to affordable housing at the start of the academic year may have a positive impact on students' grades and degree progression. To my knowledge, this paper is the first to exploit exogenous variation in the timing of access to affordable and stable student housing and examine its impacts on educational outcomes in a university setting. Furthermore, it explores whether the effects differ across types of students, since some groups may benefit more from early hous-

²Previous research has shown that such factors can have a notable effect on students' outcomes (Card, 1995; Nonis and Hudson, 2006; Rothstein, 2007; Callender, 2008; Wenz and Yu, 2010; Darolia, 2014; Baert et al., 2018).

ing access than others. I also investigate some mechanisms through which the effects may arise. The results have important policy implications, as the potential effects on study performance may impact human capital accumulation and long-term economic outcome (Card, 1999; Zhang, 2008; Freier et al., 2015; Kirkeboen et al., 2016).

For the analyses, I use unique data from a housing lottery in one of Sweden's largest university towns, Lund, combined with Swedish register data. The lottery was held by a university-affiliated company before the start of the academic year 2022/2023 and assigned a random rank to each of the 2,546 participants who were newly admitted university students. Every participant remains eligible to receive AF housing regardless of their rank. What the ranks determine is each participant's priority in the queue, and therefore how quickly they receive an offer, effectively randomizing the timing of access to student accommodation rather than access itself. Additionally, I use university register data to measure students' academic results. Linking these datasets enables me to estimate the impact of exogenous variation in when a student obtains student housing, specifically whether this happens by the start of the academic year, on educational outcomes, and to explore which students were most affected. Furthermore, I conducted monthly surveys among lottery participants to investigate the channels through which they might have been impacted.

The results show that having a better lottery rank strongly increases the probability of having student accommodation at the beginning of the studies and that in general, a better rank is associated with a shorter waiting time. Given the supply of housing units each month, participants with the first 200 positions in the rankings would be more likely to receive affordable student accommodation before the start of the semester. I therefore use this top 200 lottery rank indicator as an instrumental variable (IV) for whether a participant secured accommodation before the start of the academic year. This lets me exploit the exogenous variation in accommodation timing to study the impact of early access to student housing on grades. My main results show a positive causal effect of residing in affordable student housing at the start of studies on standardized grades, equivalent to an increase of 23% of a standard deviation, a notable effect in magnitude. Moreover, early access to student accommodation units increases the probability of ranking in the top 5 and top 10 percentile of a course grade distri-

bution by approximately 27% and 34%, respectively. I find no clear evidence that early access to housing speeds up degree progression or reduces the probability of dropping out.

Using the data collected by the survey, I then investigate potential mechanisms. Participants who secured student accommodation at the onset of their university studies are less likely to work full-time, with the probability falling by 2 to 6 percentage points depending on the sample. This is a potential mechanism affecting educational outcomes. While student employment can be a complement to education through learning-by-doing, most studies have found negative and in some cases non-linear effects of student employment on academic achievement (Stinebrickner and Stinebrickner, 2003; Kalenkoski and Pabilonia, 2010; Neyt et al., 2019). I also find that students who did not receive student accommodation are more likely to live outside of the city of Lund, where the university is located. Long commutes have been shown to be associated with less engagement in education, which in turn has been found to negatively affect students' academic achievement (Braxton and Hirschy, 2005; Kuh et al., 2008; Kobus et al., 2015). While access to student housing decreases the probability of living with roommates, it does not affect how often students meet up with their peers for social purposes. Lottery participants who gained early access to student housing also experience greater housing stability, measured by the duration and type of their rental contract.

This paper contributes to several strands of literature. It is most closely related to research on the causal determinants of college performance and success, particularly the small literature on student living arrangements. Reynolds (2020) finds that living in on-campus dormitories increases GPAs but has no effect on student retention, while Turk and González Canché (2019) find no effect on associate degree completion.³ These studies focus on on-campus housing, where student integration and peer interactions are likely to be important mechanisms. This paper instead studies a setting without on-campus housing, where housing stability and financial burden are the more plausible

³Reynolds (2020) uses an instrumental variables design that exploits university residency rules, which create exogenous variation in students' likelihood of living in on-campus housing. Turk and González Canché (2019) instead use propensity score methods to compare similar students who do and do not live on campus.

channels. Because participants are competing in the open rental market rather than a dormitory system, employment is a natural margin of adjustment for students without stable housing. In addition, this paper documents a direct labor market response, an outcome that previous work on student housing has not examined.

More broadly, research on policies and factors aimed at improving college retention, degree completion, and academic performance among university students has produced mixed results. Studies indicate that academic support services, financial aid, grade incentive programs, adjunct instructors, and increased faculty-student engagement can improve academic achievement (Angrist et al., 2009; Bettinger and Long, 2010; Angrist et al., 2014; Carrell and Kurlaender, 2023; Murphy and Wyness, 2023). Additionally, psychological interventions designed to enhance students' mindsets and sense of belonging have shown positive effects on grades, particularly for disadvantaged groups (Walton and Cohen, 2011; Murphy et al., 2020). However, other interventions, such as providing performance feedback, have been found to negatively impact grades (Azmat et al., 2019), while coaching focused on mental health and study time, as well as increases in tuition fees, have shown no significant effects on educational outcomes (Fricke, 2018; Oreopoulos and Petronijevic, 2019). This paper adds to this literature by examining access to affordable student housing as another potential determinant of academic success.

The paper also contributes to the small but growing literature on housing lotteries and waiting lists. The student housing lottery provides a credible source of exogenous variation to estimate the causal effects of housing on educational outcomes, as well as other outcomes such as employment. Previous studies have mainly examined access to social housing. While some evidence suggests that lottery winners experience improvements in housing quality, income, and education over three to five years (Kumar, 2021), other studies find that these gains are concentrated among households that obtain housing in high-income neighborhoods (Van Dijk, 2019). Moreover, Öst and Johansson (2023) show that randomly receiving a rent-controlled apartment in Sweden reduces annual income and employment. What sets this paper apart from previous studies in the field of housing lotteries is that it focuses on university students, whereas previous research has predominantly examined family units. University students represent a unique de-

mographic with different priorities and challenges. Their academic performance, time management, and decisions such as whether to work during their studies are likely more sensitive to housing stability and timing.

More generally, this paper contributes to the literature that assesses the role of in-kind transfers in educational achievement. In this context, opting for student housing is cheaper than renting accommodation in the private housing market, thus it incorporates an element of in-kind transfer. Previous studies examining the effects of different welfare programs, specifically in-kind transfers, on recipients' life outcomes have yielded varied conclusions. Evidence on the educational effects of these programs is mixed, with some studies reporting positive effects on the academic performance of low-income children and others finding little or no effect on students' grades (Currie, 1994; Jacob et al., 2015; Chetty et al., 2016). Lundborg et al., 2022 and Bütikofer et al., 2018 find that the provision of free and universal nutritious food in schools has positive effects on health and educational attainment in early adulthood. This paper examines whether subsidized student housing, viewed as an in-kind transfer, affects academic achievement among university students.

The remainder of the paper proceeds as follows. Section 2 introduces the student housing lottery and the process for participating in it. Section 3 outlines the data and the survey. Section 4 describes the empirical strategy. Section 5 presents the main estimates of the effect of student housing on educational outcomes. Section 6 examines heterogeneity across student groups. Section 7 explores the mechanisms driving these effects. Section 8 reports robustness checks. Section 9 concludes.

2 AF Bostäder housing lottery

In this section, I describe the institutional context, the types of housing available to students, and the structure and rules of the lottery system, including how students can participate, the conditions they must meet, and the implications of their lottery results.

Lund Municipality, in southern Sweden, is a quintessential student town: with roughly 46,000 students enrolled at Lund University against a municipal population of about 130,000, students make up close to a third of the local population. Founded in 1666,

Lund University is consistently ranked among the top three universities in Sweden (QS World University Rankings, 2024) and is among the country's largest (Swedish Higher Education Authority, 2023). It offers undergraduate and graduate programs in both English and Swedish and, through partnerships with over 600 universities worldwide, hosts several hundred exchange students each year. Admission to the university's programs follows a fixed annual calendar. The academic year has two semesters, starting in early September and mid-January. Fall admissions consist of two rounds. An international round which announces results by April, and a second round, for Swedish, EU, and EEA students, which announces results by July.⁴ By then, the university applicants know whether they have a place and in which program, roughly two months before the semester begins.

Newly admitted students still face the matter of finding somewhere to live before the semester begins. The large student population in Lund Municipality has contributed to a significant housing shortage and rising rents in recent years (see Figure A1a and Figure A1b). Students have three primary options for securing housing, each based on different eligibility criteria. The first is LU Accommodation, which is part of Lund University and offers off-campus housing in Lund, Helsingborg, and Malmö. Although LU Accommodation does not own these properties, they work with private landlords, and the contracts are always signed directly between the student and LU Accommodation. This type of housing is available to students from countries outside the EU/EEA who generally have to pay tuition fees and are eligible for LU Accommodation on that basis. Students from the EU/EEA, along with PhD candidates, who do not have to pay tuition, are therefore not eligible for LU Accommodation.

The second option is the private housing market. Sweden has a heavily regulated rental market that mostly operates on a queue-based system. Individuals join a city's rental queue, and when a unit becomes available, whoever has been registered longest has priority to claim it. Newer applicants are placed behind those who have already waited months or years for a first-hand contract.⁵ This creates a real problem for incoming

⁴The EEA (European Economic Area) includes all EU member states along with Norway, Iceland, and Liechtenstein, allowing these countries to participate in the EU's internal market without being EU members.

⁵In Sweden, first-hand rental contracts are leases directly between tenants and property owners, offering long-term tenancy rights and stability. These contracts typically provide stronger legal protections

students. Admission results are announced in either late March or July. That leaves only a few weeks before the semester begins in September, and a student who learns of their admission this late starts at the very back of that same queue. It is also likely that some incoming international students are unaware of the queue-based rental system, and this can make it even more challenging for them to secure housing. Therefore, both international and Swedish students often turn to alternatives outside the queue altogether, such as unofficial Facebook groups and housing websites, where landlords sublet privately or offer second-hand contracts directly. These arrangements can be secured immediately without any queue time, but they typically come with less legal protection, shorter or uncertain tenancies, and rents that are mostly higher and not subject to the same regulation as first-hand contracts.

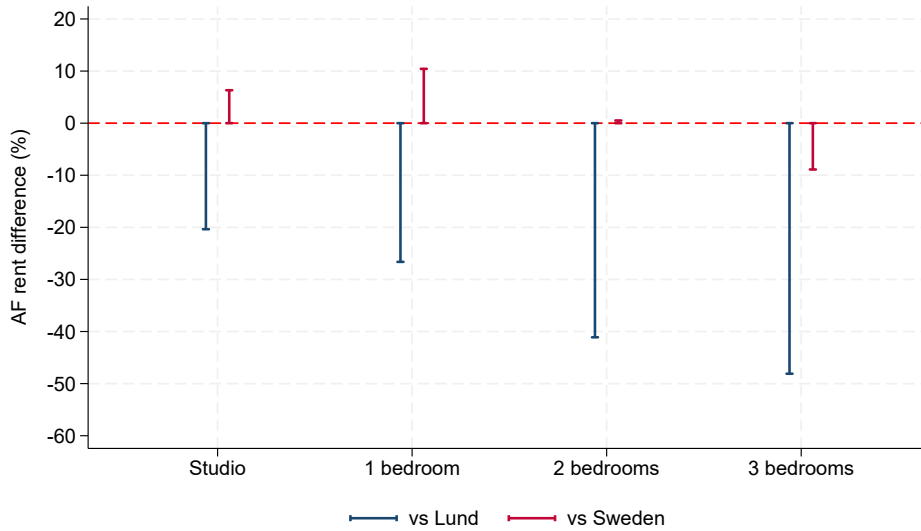
The third option is through AF Bostäder, a university-affiliated company. All newly admitted students are eligible to apply for housing through this service, regardless of whether they are Swedish or international. AF Bostäder (AF) is a non-profit foundation located in Lund Municipality, Skåne, and the largest student housing provider in southern Sweden. It offers over 6,000 housing units across various residential areas in Lund, nearly half of which are corridor rooms with shared communal areas such as a kitchen and living room, and the rest apartments with one to four rooms. AF's units are centrally located, close to the university, and rented out under secure first-hand contracts. Above all, though, what makes them so sought-after is the rent. A studio typically costs around 20 percent less than a comparable apartment on Lund's private market, and the gap widens further for larger apartments (see Figure 1).⁶ Given these advantages, AF units are highly attractive to students, and each summer AF holds a lottery among newly admitted students to determine the order in which they get access to them.

The lottery works as follows. Students who have not lived in Skåne in the past 12 months and have not previously studied at Lund University are considered eligible to

for tenants, including regulated rent increases and security of tenure.

⁶Lund rents reported in Figure 1 are based on advertised listings from private rental platforms and therefore do not include rent-controlled units allocated through the municipal housing queue. While rents for these units may be lower, obtaining them typically requires several years in the queue and is therefore not a realistic option for the lottery sample, which consists of newly admitted students who had not lived in the Skåne region during the previous year.

Figure 1: Rent comparison



Notes: This figure shows the percentage difference in average monthly rent between AF's student housing and rental housing in Lund Municipality and across Sweden, by apartment type. The Swedish rent data is sourced from Statistics Sweden and Lund rents are based on advertised listings from multiple rental platforms. All data belongs to the year 2023.

participate in the lottery and may register for it during a two-day window in July, after admission results are announced but before the academic year begins. Once registration closes, AF draws the lottery and assigns each participant a date and time stamp in the format *YYYY-MM-DD HH:MM*, generated at random by AF's own IT system.⁷ An earlier stamp means a better queue position, and therefore higher priority when units become available. Participants are not shown one another's timestamps, and the range of possible values is not disclosed, so students have no way of knowing whether their own result is "good" or "bad" in absolute terms.⁸ What the lottery assigns is a rank within a single, shared queue, not a yes-or-no outcome.

It is worth being explicit about what this means: there are no *losers* in this lottery. Every registered student is entered into the same queue and remains eligible to receive an AF unit for as long as they are willing to wait so nobody is excluded or rejected as a result of the lottery itself. A worse draw means a longer expected wait, not disqualification. Since queue position is assigned at random and is unrelated to the students'

⁷The random lottery numbers are generated in-house by AF Bostäder's IT system using standard Java programming. A random number is assigned and then converted into a queue date, starting from the earliest possible time for new students.

⁸While students could compare their timestamps with one another, this is unlikely, as they typically would not have met before the semester starts.

characteristics, it provides a natural instrument for the *timing* of housing access, while eligibility for housing itself is never at stake. This feature is exactly what I exploit later in the paper to identify causal effects.

Once the lottery has been drawn, students do not automatically receive housing. They must actively apply for it. AF lists available units on its website, and lottery participants who want a unit must express interest and apply during that unit's specific application period. Priority among applicants is solely based on the queue position assigned by the lottery, not the time of application. The student with the best queue position (earliest timestamp), among those who applied, receives a contract proposal from AF, which they may accept or decline (see a hypothetical example in Figure A2). Students are limited to applying for only three available units at any given time, and each application is binding. Once a unit is allocated to an applicant, their queue position is de-registered. Although students may decline a contract proposal, doing so costs them their lottery rank and their chance to be considered for any other unit offered through the lottery.

In the 2022/2023 academic year, nearly 7,500 students began undergraduate and graduate studies at the university in the Fall semester. Of these, 2,546 registered for the AF housing lottery and were assigned a random queue position.⁹ Starting in August, AF made units available to lottery participants each month. Table 1 reports the number of units released each month specifically to lottery participants. As a result, 208 students had secured AF accommodation by the start of the academic year, before September 2022, and by the end of the academic year in July 2023, this number had increased to 982.

Figure 2 shows the full distribution of days between the lottery and move-in date, which is also in line with the number of units released for application each month shown in Table 1. Since the data cover housing contracts only up to May 1, 2023, the figure includes only those participants who had secured a unit from AF by that date. Most secure housing within roughly two to three months, though a smaller share waits

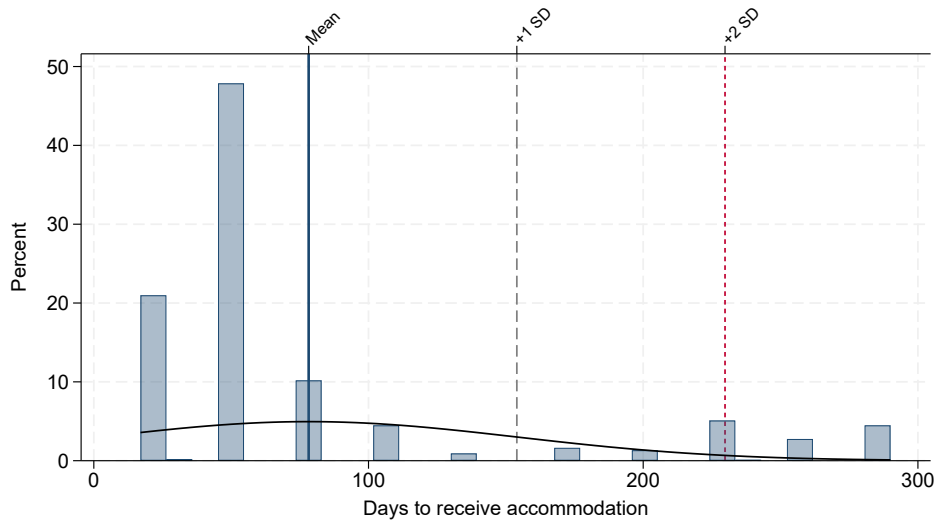
⁹Not all newly admitted students are eligible for or in need of the lottery. Continuing students, tuition-paying students who are eligible for LU Accommodation, and students who had already secured housing on their own before registration opened would not have registered.

Table 1: Available units and move-in times

	(1) # of participants receiving units	(2) # of available units for rent
August	208	213
September	470	500
October	100	109
November	44	44

Notes: The table above shows the number of units released by AF each month for lottery participants, along with the number of students whose contracts began in each respective month during 2022.

considerably longer.

Figure 2: Number of days between lottery and move-in date histogram

Notes: This figure shows the distribution of the number of days it took for lottery participants to secure student housing. The sample includes participants who obtained housing from AF by May 1, 2023, the end of the observation window.

3 Data

This paper combines four main sources of data: AF Bostäder's lottery and housing records, Ladok's educational register, a survey administered to lottery participants, and Statistics Sweden's administrative register data. After collecting the lottery, educational, and survey data, they were sent to Statistics Sweden, where they were anonymized, each participant was assigned a distinct identifier, and the data were linked to the administrative registers, which provide demographic information. Each source is de-

scribed in more detail below.

3.1 Lottery outcomes

In collaboration with AF Bostäder, I gather novel data on queue positions and rankings of lottery participants, as well as their accommodation status, including whether and when they secured a unit from AF Bostäder. This dataset includes details such as location, type, and size of the accommodation. Knowing not just whether but exactly when each participant moved in lets me observe how a student's queue position translates into the timing of their access to housing. Later in the analysis, I use this information, together with each participant's lottery rank, to construct my main treatment variable which is an indicator for whether a participant had already secured AF accommodation by the start of the academic year in September 2022.

The data covers housing contracts for lottery participants from August 1, 2022, to May 1, 2023. Over this period, 982 participants received student housing through AF. AF began releasing units to lottery participants in August 2022, with roughly 200 units available before the start of the academic semester in September (see Table 1 for the exact monthly figures). It is this roughly 200-unit threshold, and the corresponding queue position it implies, that later defines the instrument used in the empirical strategy.

3.2 Educational outcomes

This study uses detailed, course-level grades and class rankings for lottery participants. This would allow a more granular analysis of academic performance than a simple degree-completion measure would. The main outcomes capture this performance in three ways: average standardized grades, which measure how a student performs relative to their classmates across all courses taken; the share of courses in which a student ranks among the top 5 percent of their class; and the share in which they rank among the top 10 percent. Together, these outcomes let me assess not just whether housing access affects average performance, but whether it moves students into the upper end of the grade distribution.

To construct these educational profiles, I collect register data from Ladok, Sweden's national system for recording students' educational histories. Ladok provides comprehensive educational metrics, including individual and peer performance indicators such as grades, enrolled courses, credits earned, examination dates, and fields of study.¹⁰ The data spans up to July 2023, the end of the lottery participants' first academic year.

This study focuses on courses with a detailed grade scale, rather than those graded only pass or fail. Even for courses with a detailed scale, the data cannot distinguish a student who took the exam and failed from one who dropped the course, postponed it, or never sat the exam at all. The same ambiguity applies to pass/fail courses. Because of this, the data cannot be used to study the pass/fail margin itself. What it can be used for is comparing grades and rankings among students who completed a course and received a grade. Passing at least one course in the first year, dropout, total credits passed, and days to the first exam taken are instead examined separately, as extensive-margin outcomes, in Section 5.¹¹ Grades on the A-E scale are converted to their equivalent percentage ranges, with each letter grade represented by the mean value of its corresponding range (see Table A1). Both the converted grades and those initially given on a percentage scale are then standardized, and the resulting standardized grades are combined into the first main outcome, average standardized grades, by weighting each course's grade by its number of credits (ECTS).^{12,13} Since ECTS credits reflect the workload and relative importance of each course, they are used to weight the grades when calculating this average. This is because ECTS credits are designed to standardize student workload across courses and institutions in Europe, with each credit representing approximately 25 to 30 hours of total work, including lectures, assignments, and self-study. As a result, courses with more ECTS credits require a higher workload and have a larger influence on a student's overall academic performance. All

¹⁰Field of study is not available for exchange students, and is therefore used as a control only in some analyses.

¹¹It is also worth noting that a course being absent from the detailed-grade sample does not necessarily mean it was graded pass/fail by design. Some courses with a nominally detailed scale are recorded in Ladok with only a pass outcome for a given instance, for reasons not fully observable in the data.

¹²The grade standardization was done separately for each course and using all of the students who took the exam for a certain course. However, the sample used in the analysis is the sample of lottery participants. Therefore the mean of the grades is no longer 0 across the used sample.

¹³ECTS: European Credit Transfer and Accumulation System credits

steps are done separately for the first two semesters and cumulatively for the entire first year. The cumulative first-year measures are the main outcomes throughout the paper, while the semester 1 and semester 2 measures are examined separately later to check whether any effect is concentrated in a particular part of the year.

The two remaining main outcomes, the top 5% and top 10% shares, are built from the same standardized grades. For each course, a student's standardized grade determines their rank in that course, and a dummy variable is set to one if their grade falls within the top 5% of the class, or within the top 10%, with a separate dummy for each threshold. As with average grades, these dummies are then weighted by each course's credit value and averaged across all of a student's courses. The resulting variables, which will be referred to as "top 5%" and "top 10%" for simplicity, are therefore not simple 0/1 indicators but the credit-weighted share of a student's courses in which they ranked among the top performers.

3.3 Survey

Two surveys were designed to shed light on the potential mechanisms through which housing access may affect educational outcomes.

Survey I, illustrated in Figure A7, was sent to all lottery participants in July 2022 via email on the day the lottery results were announced and before the housing units became available for application submissions. Participants were asked to identify the most important aspect of accommodation for them, with options including rent, distance to faculty, size, and state of the building (e.g., newly renovated). Moreover, they were requested to rank their accommodation preferences from 1 to 4, the most preferred being 1. The available AF housing options that they had to rank consisted of corridor rooms, studio apartments, one-bedroom apartments, and two-bedroom apartments. They were reassured that participation in this study is voluntary and will not affect their position in AF housing queue, accommodation eligibility, and accommodation allocation.¹⁴ After excluding invalid and duplicate responses, 182 students participated (equivalent to a response rate of 7.1%). Among these, 59% were women, and

¹⁴To boost participation, participants were informed in the survey email that twenty cinema tickets would be offered to ten randomly chosen respondents.

80% were enrolled in a bachelor's program. The statistics shows that 46% of participants considered rent the most important factor for housing, followed by 41% who prioritized distance to faculty. The most preferred type of accommodation was studio apartments, with nearly half of the participants selecting it as their top choice (see Table A16 in the appendix).¹⁵ Survey I is used purely descriptively: since it was administered before any lottery outcome had been realized, it is not intended to establish a causal relationship on its own, but rather to give a sense of which housing characteristics students themselves consider important when evaluating a place to live, and whether students have clear preferences over these characteristics at all. This descriptive information later helps in interpreting the mechanisms by indicating which features of housing are most likely to matter to students in the first place.

Survey II, as shown in Figure A8, was sent to all lottery participants every month from September 2022 to February 2023. Unlike Survey I, which is used purely descriptively, Survey II's outcomes are used directly in the main analysis. Its main purpose is to examine whether labor market and housing-related outcomes differ between lottery participants whose rank was not good enough to receive AF housing at the start of the semester and those who did receive it. Each month, participants report the location, duration, and type of their current housing contract, along with the required notice period (i.e., the amount of time a tenant must provide before ending their rental agreement) which are measures providing insights into students' housing insecurity. Additionally, both groups, those in AF housing and those not, were asked about their time spent on social activities and part-time or full-time jobs, to understand how they allocate their time outside of studying. These outcomes are used directly in the empirical analysis to help disentangle some of the potential mechanisms through which early housing access may affect educational outcomes.¹⁶ Over the survey period, a total of 1,641 responses were received from 874 unique individuals, resulting in a response rate of 34.33%.¹⁷ Table A17 reports descriptive statistics for these respondents. On av-

¹⁵Due to the small number of individuals who participated in Survey I, its results are not used to draw strong conclusions and should be interpreted with caution.

¹⁶To encourage participation, participants were informed that one randomly selected respondent would receive a 1,000 Swedish Krona (approximately \$100) Amazon Sweden gift card at the end of each survey.

¹⁷The number of participants in Survey II for each month from September to February is 256 (10.05%), 336 (13.20%), 455 (17.87%), 229 (8.99%), 141 (5.54%), and 224 (8.80%), respectively.

erage, they are 22 years old, 57% are female, and 77% have at least one parent with a university degree. Around 15% report being employed, either full- or part-time, at the time of the survey.

3.4 Register data

In parts of the analyzes, the population register from Statistics Sweden is used to add comprehensive information on the demographics, employment status, income levels, and parental background of the lottery participants. This register includes data on participants who have been living and are registered in Sweden, primarily consisting of Swedish nationals.

For 1,149 of the participants, which is about 45% of the total number of lottery participants, I am able to obtain detailed data on individual characteristics such as age, gender, nationality, employment status, income, and city of residence. In addition, information on their parents' backgrounds is collected, including the highest level of education, income, age, and city of residence. Data for the remaining participants are unavailable since many had recently moved to Sweden from other countries and their information was not collected or stored in Swedish registers.

3.5 Sample selection and descriptive statistics

Table 2 summarizes how the sample is constructed, starting from all students admitted to the university and narrowing down to the samples used in the analysis. Of the 7,443 students admitted for the 2022/2023 academic year, 2,546 registered for the AF housing lottery. Of these lottery participants, 2,336 (92%) could be linked to educational records, and 2,315 (91%) passed at least one course in their first year. Among lottery participants, 1,601 (71%) have a granular grade registered in the first year and form the All sample described below.

The *All* sample consists of these 1,601 lottery participants who completed at least one course with a detailed grade in the 2022/2023 academic year. Among these participants, 208 secured AF accommodation by September 2022, while others obtained housing through AF later in the year or not yet until May 2023.

The *Restricted* sample further requires full demographic data and information on field of study to be available, leaving 635 participants. This is the sample used whenever control variables or field-of-study fixed effects are included in the specification.

The *Swedish* sample is the subset of the Restricted sample consisting of Swedish participants, leaving 608 participants.

The *Newcomer* sample consists of the 891 participants with a detailed grade registered in the first academic year but with no demographic data available in the Swedish administrative registers. This is most likely because they have recently entered the country and hence, do not yet appear in Statistics Sweden's population register, which is why they are referred to as newcomers.

Of the 1,601 participants in the All sample, 560 also responded to Survey II and that provides the subsample used to analyze the survey-based mechanisms outcomes described earlier. Table A2 checks whether lottery rank predicts a student's probability of appearing in each analysis sample. Lottery rank does not predict appearing in the first-semester, second-semester, or first-year samples, which the main analysis relies on. However, having a lottery rank smaller than 200 increases the probability of participating in the survey by 8.2 percentage points, a result that is statistically significant at the 5% level. This will be discussed further in Section 7.

Table 2: Sample structure and statistics

	(1) N	(2) % of lottery participants	(3) Mean	(4) SD
Admitted incoming students	7,443			
Lottery participants	2,546	100		
Linked to education records	2,336	91.75		
Pass at least one course in the 1 st year	2,315	90.93		
With granular grades in the 1 st year	1,601	62.88		
Complete demographics data	1,149	45.13		
Unique survey respondents	874	34.33		
With accommodation by September	208	8.17		
Days to get accommodation			78.21	75.79

Notes: The table above shows the number of students admitted to the university and the number of those who participated in the lottery. Lottery participants are then categorized into different samples based on specific criteria. Percentages in column (2) represent the share of lottery participants in each category. Column (3) and (4) include the means and standard deviations, respectively.

Table 3 reports descriptive statistics for the All and Restricted samples, and further splits the Restricted sample into Survey II respondents and non-respondents. Across all samples, participants are on average around 20 years old, and close to half are female. About 8% have a lottery rank below 200. Parental education levels are nearly identical between respondents and non-respondents, though non-respondents' parents report somewhat higher average income. Educational characteristics are also comparable, with similar average grades, top 5, and top 10 outcomes across the two groups. The main differences are that non-respondents are somewhat more likely to be employed and to receive a study grant, and report a higher average income in the year before the lottery, than respondents.

Table 3: Descriptive statistics

Sample:	(1) All		(2) Restricted		(3) Survey respondents		(4) Non-respondents	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Individual characteristics								
Age	19.81	1.96	19.63	1.57	19.69	1.73	19.59	1.47
Female	0.50	0.50	0.44	0.50	0.45	0.50	0.43	0.50
Immigrant			0.04	0.20	0.05	0.21	0.04	0.20
Employment status ($t - 1$)			0.63	0.48	0.57	0.50	0.67	0.47
Skåne resident ($t - 1$)			0.00	0.00	0.00	0.00	0.00	0.00
Study Grant ($t - 1$)			0.79	0.41	0.74	0.44	0.81	0.39
Annual income ($t - 1$)			990.03	927.14	1068.13	1077.52	945.37	827.15
Lottery rank (= 1 if < 200)	0.08	0.27	0.08	0.27	0.09	0.29	0.07	0.26
Parents' characteristics								
Mother's education			4.64	0.83	4.63	0.81	4.65	0.84
Father's education			4.59	0.98	4.57	1.03	4.60	0.94
Father's income			8160.67	9604.44	7531.70	6904.43	8520.31	10842.37
Mother's income			6008.68	4024.47	5525.96	2969.11	6284.69	4498.77
Mother living in Skåne			0.01	0.08	0.00	0.00	0.01	0.10
Father living in Skåne			0.01	0.10	0.02	0.13	0.01	0.09
Educational characteristics								
Graduate student			0.05	0.22	0.03	0.17	0.06	0.25
# of credits registered			55.05	11.93	55.40	10.98	54.86	12.46
Average standardized grades	0.03	0.68	0.05	0.65	0.01	0.67	0.08	0.63
Top 5	0.33	0.28	0.30	0.26	0.29	0.27	0.30	0.25
Top 10	0.38	0.29	0.36	0.27	0.35	0.27	0.36	0.27
# of observations	1,601		635		231		404	

Notes: The table presents the means and standard deviations of characteristics for lottery participants, divided into three samples. The restricted sample includes all lottery participants with available demographic data. This sample is further divided into survey respondents and non-respondents. Annual earnings are measured in 100 Swedish SEK (SEK 100 is equivalent to approximately 8.5 EUR as of July 2024). Variables average standardized grades, top 5 and top 10 are calculated as explained in section 3.2.

4 Empirical strategy

The primary objective of this study is to examine the potential effects of residing in student housing by the start of the semester on educational outcomes. I estimate the effects using the following model:

$$y_i = \alpha + \delta AC_i + \beta X_i + \gamma_f + \epsilon_i \quad (1)$$

where y_i represents the different educational outcomes of lottery participant i . AC_i is an indicator variable equal to 1 if lottery participant i has secured a student housing contract that started before September 2022, when the first semester officially begins. In some specifications, I also control for a series of characteristics, contained in the vector X : students' age, gender, an indicator for being Swedish, lagged income and employment status, an indicator for enrollment in a graduate program, parents' highest level of education achieved, parents' income, and indicators for parents living in Skåne. γ_f represents field of study fixed effects, which are included only in specifications that exclude exchange students, since field of study is not observed for this group. Later in the analysis, I also explore whether receiving accommodation in subsequent months has any impact.

Estimating δ directly by OLS is unlikely to recover a causal effect. Whether a student has AF housing by September depends not only on their lottery rank, but on whether they choose to apply for and accept a unit once one becomes available. Some participants with a good rank do not apply, likely because they have already secured housing through other means. Comparing students with and without AF housing by September therefore does not isolate the effect of housing timing alone. It also reflects selection into applying, which likely correlates with a student's outside options, such as family ties in Lund or the resources to quickly secure private housing. These outside options could independently affect academic outcomes. To address this, I exploit the AF Bostäder housing lottery, which randomly assigns priority in the housing queue. As discussed in Section 2, every lottery participant remains eligible to receive AF housing regardless of their rank: a worse rank means a longer expected wait, not exclusion from ever receiving a unit. The variation I exploit is therefore in the *timing* of accom-

modation, not in whether a student ever receives one. Before the 2022/2023 academic year began, more than 200 units of student accommodation became available to lottery participants, as shown in Table 1. This means around 200 participants could have received housing before the semester began. I let q_i denote participant i 's lottery rank and construct a binary instrument, $q_i < 200$, equal to 1 if a participant's rank is among the top 200. Because this instrument does not perfectly determine AC_i , as some participants do not comply with the priority assigned to them, I use an instrumental variable (2SLS) framework rather than treating the rank cutoff as a direct treatment assignment. The first stage is given by

$$AC_i = \pi_0 + \pi_1 \mathbb{1}[q_i < 200] + v_i, \quad (2)$$

where $\mathbb{1}[q_i < 200]$ is the instrumental variable, and equation (2) is estimated jointly with equation (1) using 2SLS to estimate δ .

Using this framework, I estimate the local average treatment effect (LATE) of receiving housing by the start of the semester, relative to receiving it later, or not yet, within the observation window. This effect applies to the sample of “compliers”, participants whose probability of receiving accommodation by September is influenced by their lottery rank. Some participants may be “never-takers”, meaning they do not receive accommodation by September regardless of their rank, though they, like everyone else in the lottery, remain eligible to receive AF housing later. These never-takers may have personal preferences, other commitments, or circumstances that lead them not to accept an accommodation offer before the semester begins.

Randomization: A key identifying assumption for this analysis is that the housing lottery creates exogenous variation in access to student residential units. If the lottery rank was endogenous, one might expect it to be predicted by pre-determined characteristics of the participants. Table A3 shows that this is not the case for either the entire sample with available characteristics data, nor for the sample of survey respondents and non-respondents separately. Of the 33 regressions of different characteristics on the lottery rank, only one is significant at a 1% level. Furthermore, a series of joint F-tests confirm that the set of predetermined characteristics does not predict the lottery

rank.

Relevance: To investigate the strength of the instrumental variable in predicting the probability of having accommodation at the beginning of the university studies, I estimate the first-stage results separately for each of the main samples. Table 4 shows that in all samples, the indicator for having a lottery rank below 200 is strongly correlated with having accommodation by September. Specifically, a lottery rank below 200 increases the probability of obtaining accommodation by 62 percentage points for the All sample. The F-statistics are high in all columns, confirming instrumental relevance.¹⁸ The coefficients are not equal to one for two reasons. First, not every participant with a rank below 200 applies for AF housing after the lottery. They retain their priority and remain eligible, but some choose not to apply, likely because they have already secured accommodation elsewhere. Second, a participant with a rank above 200 can still receive housing before September, if no participant with a better rank applies for the same unit.

Table 4: First-stage

	Accommodation by September			
	All (1)	Restricted (2)	Swedish (3)	Newcomers (4)
Lottery rank (=1 if < 200)	0.6165*** (0.0329)	0.5838*** (0.0563)	0.5696*** (0.0593)	0.6279*** (0.0430)
Mean	0.29	0.29	0.29	0.30
# of observations	1,601	635	608	891
F-statistic	351.50	107.46	92.35	213.57

Notes: The table presents first-stage estimates of the relationship between the likelihood of having student accommodation by September and lottery rank across the different samples. The reported F-statistics are robust Wald F-statistics for testing instrument strength. Robust standard errors are shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Monotonicity: The monotonicity assumption implies that having a better lottery rank should move the probability of obtaining student accommodation for all participants in the same direction. In this case, having a better rank should increase the probability of having accommodation by September for all students, regardless of their rank. How-

¹⁸For the first-stage plot, see Figure A4

ever, one might argue that participants with better ranks could become aware of their higher priority and decide to wait for their preferred type of accommodation to become available. If this were the case, the monotonicity assumption would be violated, since these better-ranked participants would end up with a lower probability of securing housing before September. Despite this concern, such a violation is unlikely due to the nature of the lottery system and the format of the ranks, a random date and timestamp. This structure makes it difficult for participants to realize how good or bad their rank is. Lottery participants are not informed of the start and end range of the timestamp distribution, and they also lack information about other participants' timestamps. For example, a participant might receive a timestamp like "2022-07-12 11:21:00" but has no way of knowing what the earliest possible timestamp was and therefore remains uncertain of their relative position in the lottery. This lack of information reduces the likelihood that participants with higher ranks intentionally delay their housing application.

Moreover, the goodness of a rank is not fixed; it depends on two things that participants cannot observe at the time of the lottery. The first is overall supply. If AF supplies a large number of units, then most ranks can be considered "good" and vice versa. Figure A3 shows that the number of available units has fluctuated considerably across years, from as few as 100 to as many as 250 in a given month. As a result, a rank that would have been good enough in one year might not be good enough in the next. The second is the specific pool of applicants for a given unit. A participant with a poor rank can still secure housing if nobody with a better rank applies for the unit they are interested in, while a participant with an excellent rank might not, if several participants with even better ranks apply for that same unit. Since the overall supply is not known to participants and they cannot predict the applicant pool for any given unit in advance, this potential violation of monotonicity is unlikely.

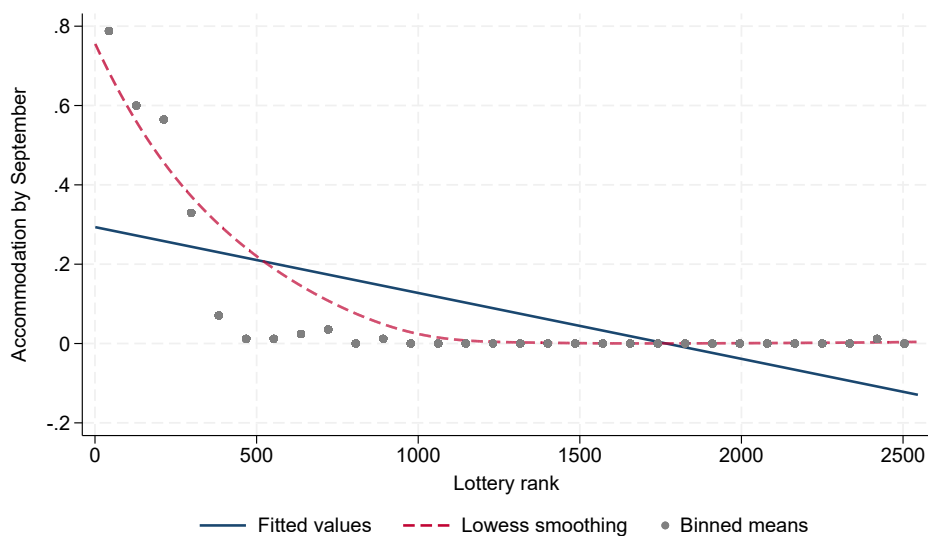
To further verify the monotonicity assumption, I plot a locally weighted regression of the indicator of having accommodation by September against the lottery rank.¹⁹ Figure 3 shows the local linear regression results of the relationship between the lottery ranks and the probability of securing student housing. The Lowess curve (locally weighted

¹⁹The lottery rank ranges from 1 to 2,546, with priority decreasing as the rank increases.

scatter plot smoothing) provides a smoothed curve that highlights the relationship between lottery ranks and the likelihood of having accommodation by September. This figure demonstrates that as the rank increases, the probability of residing in student accommodation at the beginning of the studies decreases monotonically, as expected.

Exclusion restriction: For the current IV approach to be valid, the instrument must not

Figure 3: Local linear regression



Notes: The figure above shows the Lowess (locally weighted scatter plot smoothing) regression of the likelihood of having student accommodation by September based on lottery ranks. Binned scatter points are constructed by splitting lottery rank into 30 quantile bins, so that each bin contains approximately the same number of participants.

affect educational outcomes through any means other than its impact on accommodation status. As mentioned earlier, the lottery rank itself is meaningless to participants beyond its role in determining student housing allocation. It is highly unlikely that the lottery rank is correlated with unobserved factors that influence students' academic achievement.

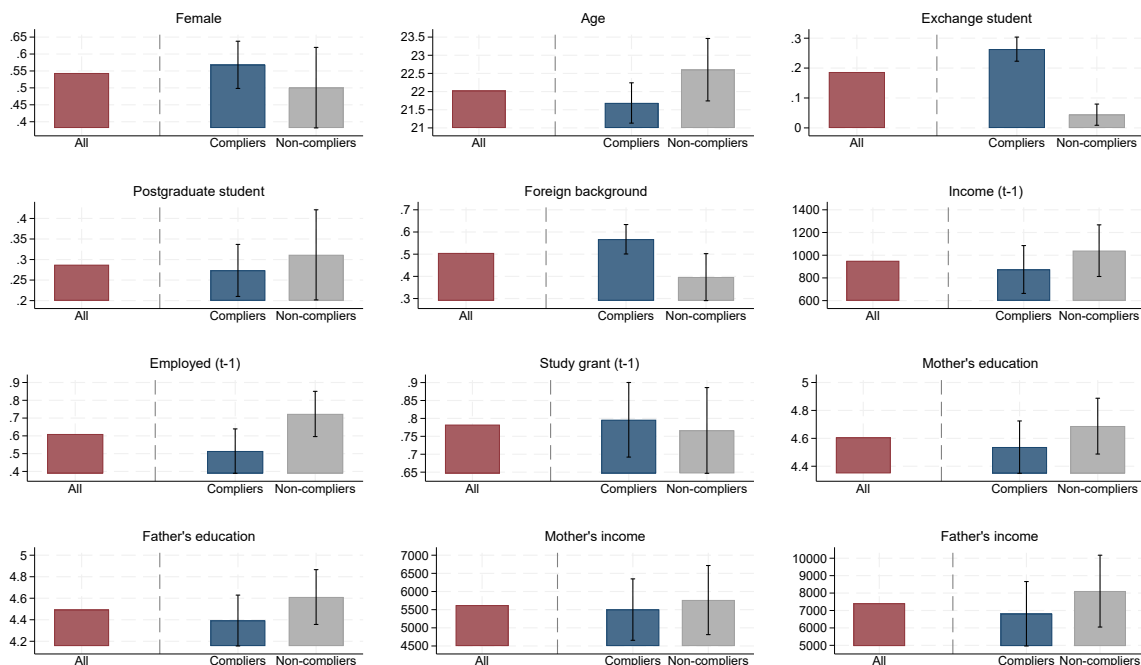
4.1 Compliers

To describe the population of students whose accommodation status by September is actually driven by the instrument, the compliers, I follow Abadie (2003). Compliance cannot be observed at the individual level. Consider a student with a good lottery rank who secures housing by September: this could be because their good rank caused them to get housing (a complier), or because they would have gotten housing regardless of

their rank (an always-taker). Since each student is only observed under the lottery outcome they actually received, it is impossible to tell these two types apart for any single student. Therefore, I do not try to identify compliers individually. Instead, I use a reweighting of the sample that recovers the average characteristics of the complier subpopulation as a whole. The methodology is discussed in Section C.

Figure 4 reports the sample mean for all participants alongside the kappa-weighted mean of compliers and non-compliers with 95% confidence intervals, for each background characteristic. Two patterns stand out. Compliers are somewhat younger than non-compliers, and they are considerably more likely to be exchange students and to have a foreign background. They are also less likely to have been employed in the year before the lottery and report somewhat lower prior income. Together, these patterns suggest that compliers are participants with fewer existing ties to Lund at the time of the lottery, more likely to be new to the city or the country, and less likely to already have a job or an income.

Figure 4: Characterizing the compliers



Notes: The figure compares predetermined characteristics across three groups: all lottery participants, compliers, and non-compliers, where compliers are participants whose accommodation status by September is determined by their lottery rank. Compliers and non-compliers are characterized using the kappa-weighting approach of Abadie (2003). Bars show group means and capped lines show 95% confidence intervals, constructed from the bootstrap standard errors.

5 Main results

5.1 Educational outcomes

I begin the empirical analysis with the All sample (as defined in Section 3). I examine the effects of accommodation by September on average standardized grades, top 5%, and top 10%. Table 5 reports the estimates for the All sample, with reduced-form, OLS, and 2SLS estimates for each outcome.

Columns 1, 4, and 7 in Table 5 present the reduced-form estimates, which are significant for all three outcomes. A lottery rank below 200 increases average grades by 15% of a standard deviation. For the share of times a participant ranked among the top 5% and top 10% of their peers, the increases are 6 and 9 percentage points, corresponding to 18% and 23% , respectively. These results establish a strong link between lottery rank and educational outcomes.

Table 5: Effect of student housing receipt

	Average standardized grades			Top 5			Top 10		
	RF (1)	OLS (2)	IV (3)	RF (4)	OLS (5)	IV (6)	RF (7)	OLS (8)	IV (9)
Lottery rank (=1 if < 200)	0.1484** (0.0631)			0.0595** (0.0257)			0.0862*** (0.0270)		
Accommodation by September		-0.0444 (0.0591)	0.2259** (0.0994)		-0.0030 (0.0222)	0.0906** (0.0403)		0.0092 (0.0245)	0.1312*** (0.0425)
Mean (control group)	0.04	0.04	0.04	0.33	0.33	0.33	0.38	0.38	0.38
# of observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601
Controls	No	No	No	No	No	No	No	No	No
Field of study FE	No	No	No	No	No	No	No	No	No

Notes: The table illustrates estimates of different student outcomes on a dummy variable for lottery rank below 200 (Reduced Form), on a dummy variable for having accommodation by the beginning of September (OLS), and on the same dummy while instrumenting with lottery rank (IV). The estimates are using the sample of all lottery participants for whom there has been a detailed grade registered in the first academic year. The outcomes are weighted by each course's number of credits (ETCS). Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Column 2, 5, and 8 in Table 5 report the OLS estimates. None are statistically significant, and the estimated effect on average grades is even negative. This likely reflects selection into applying for an AF unit rather than the effect of housing timing itself. Among students with a good rank, some apply and accept a unit once one becomes

available, while others do not, and this choice is not random. Some of the participants who do not get this housing may already have alternative housing arranged. This selection does not consistently point in one direction, which can produce an OLS estimate that is small, noisy, or even the opposite sign relative to the true causal effect.

Columns 3, 6, and 9 report the 2SLS estimates, using lottery rank below 200 as an instrument for accommodation by September. Average grades increase by 23% of a standard deviation, significant at the 1% level. This is a substantial effect, on the higher end of the range reported in studies examining the causal effects of various interventions on student grades (Sacerdote, 2001; Dynarski, 2003; Angrist et al., 2009; Bettinger and Long, 2010). The effects on the probability of ranking in the top 5% and top 10% are also substantial, with increases of approximately 27% and 34%, respectively.

These initial results include all lottery participants with registered grades in the first academic year, regardless of the availability of their demographic and parental characteristics. Now, I narrow the analysis to the Restricted sample, which includes only participants for whom such data are available. This serves two purposes. First, it mainly focuses on Swedish students, who may have an advantage in securing housing independently due to their familiarity with the housing market and their ability to use their personal networks. Second, it allows me to assess whether including control variables affects the results. If randomization is valid, including control variables should not meaningfully change the results.

Panel A in Table 6 shows the same regressions as in Table 5, applied to the Restricted sample, which requires demographic control variables to be available and mainly consists of Swedish students. The coefficients are large and comparable in magnitude to those in Table 5, and including control variables and field of study fixed effects does not change them much. One might expect Swedish students to depend less on AF housing than other participants. They are already familiar with the local culture, language, and educational system, and have established social networks that could help them find and stabilize housing on their own, without needing early access to AF units. Panel B restricts the sample to Swedish students to test this. The results do not support this hypothesis. The coefficients in Panel B are, if anything, slightly larger than in Panel A, with average grades increasing by 38% of a standard deviation, and the probability

Table 6: Effect of student housing receipt - Samples with controls available

	Average standardized grades				Top 5				Top 10			
	RF (1)	OLS (2)	IV (3)	IV (4)	RF (5)	OLS (6)	IV (7)	IV (8)	RF (9)	OLS (10)	IV (11)	IV (12)
Panel A: Restricted sample												
Lottery rank (=1 if < 200)	0.1860** (0.0924)				0.0607 (0.0386)				0.0815** (0.0411)			
Accommodation by September		0.0438 (0.0921)	0.3436* (0.1799)	0.3095* (0.1687)		0.0151 (0.0343)	0.1121 (0.0735)	0.0973 (0.0650)		0.0314 (0.0394)	0.1505* (0.0788)	0.1408** (0.0695)
Mean (control group) # of observations	0.05 635	0.05 635	0.05 635	0.05 635	0.29 635	0.29 635	0.29 635	0.29 635	0.35 635	0.35 635	0.35 635	0.35 635
Panel B: Swedish only sample												
Lottery rank (=1 if < 200)	0.2054** (0.0908)				0.0654* (0.0380)				0.0911** (0.0406)			
Accommodation by September		0.1055 (0.0935)	0.3821** (0.1763)	0.3537** (0.1668)		0.0324 (0.0356)	0.1216* (0.0720)	0.1021 (0.0630)		0.0561 (0.0406)	0.1695** (0.0775)	0.1514** (0.0676)
Mean (control group) # of observations	0.05 608	0.05 608	0.05 608	0.05 608	0.29 608	0.29 608	0.29 608	0.29 608	0.35 608	0.35 608	0.35 608	0.35 608
Controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Field of study FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Notes: The table illustrates estimates of different student outcomes on a dummy variable for lottery rank below 200 (Reduced Form), on a dummy variable for having accommodation by September (OLS), and on the same dummy while instrumenting with lottery rank (IV, with and without controls/field FE). The estimates use the restricted sample of lottery participants for whom there has been a detailed grade registered in the first academic year and all control variables are available. The outcomes are weighted by each course's number of credits (ETCS). Panel A consists of all students with available control variables; Panel B restricts Panel A to Swedish students. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of ranking in the top 5% and top 10% increasing by approximately 42% and 48%. Early access to AF housing therefore appears to matter for Swedish students as much as for the sample overall, despite their existing local ties.

If existing local ties do not explain away the effect for Swedish students, the opposite comparison is worth examining directly: does the effect look different for students with the fewest local ties of all? Table 7 presents reduced-form and 2SLS results for the sample of Newcomers, new incoming students who were not residents of Sweden in the two years prior to the start of the academic year. One might expect Newcomers to depend more on AF housing than other participants. They arrive without an established local network, may be unfamiliar with the Swedish rental market, and cannot easily rely on family in the area to help secure alternative housing, so early access to a stable place to live could matter even more for them than for the sample as a whole. Panel A examines this for the full newcomer sample. The reduced-form and 2SLS estimates are

mostly not statistically significant, with the exception of top 10%, which increases by 32%. Despite the lack of statistical significance, the point estimates are not statistically different from the results in All and Restricted samples.

Newcomers are not a single group, however. This group consists of exchange and non-exchange students. Exchange students are enrolled at another institution and study at Lund temporarily, typically for one or two semesters, while non-exchange students are fully enrolled in a degree program here. This distinction could plausibly affect how much early housing matters. Non-exchange students have a longer horizon to benefit from a stable accommodation and a stronger incentive to integrate into university life, since their degree and future opportunities depend on it. Exchange students, by contrast, may prioritize the cultural experience of studying abroad over academic performance, and their shorter stay leaves less time for stable housing to translate into stronger social or academic integration.

Panels B and C test this by splitting the newcomer sample into exchange and non-exchange students. Among exchange students, none of the reduced-form or 2SLS estimates are statistically significant, though the point estimates remain positive. Among non-exchange students, the effects on top 5% and top 10% are statistically significant, increasing by approximately 31% and 36%, though the effect on average grades remains insignificant. The point estimates for exchange and non-exchange students are not statistically different from each other, and the exchange sample contains only 344 observations, less than half the size of the non-exchange sample, so no strong conclusions can be drawn.

Figure 5 puts the 2SLS estimates from all samples above side by side, making the results easier to compare directly. In every sample, the point estimates for all three outcomes are positive, indicating a broadly consistent positive effect of early housing access on educational outcomes.

The results so far measure academic performance conditional on having a detailed grade recorded, so they say nothing about whether housing affects who ends up in that sample in the first place. This matters. If early housing access changes whether a student drops out, passes any courses at all, takes on fewer credits, or delays their ex-

Table 7: Effect of student housing receipt - Newcomers

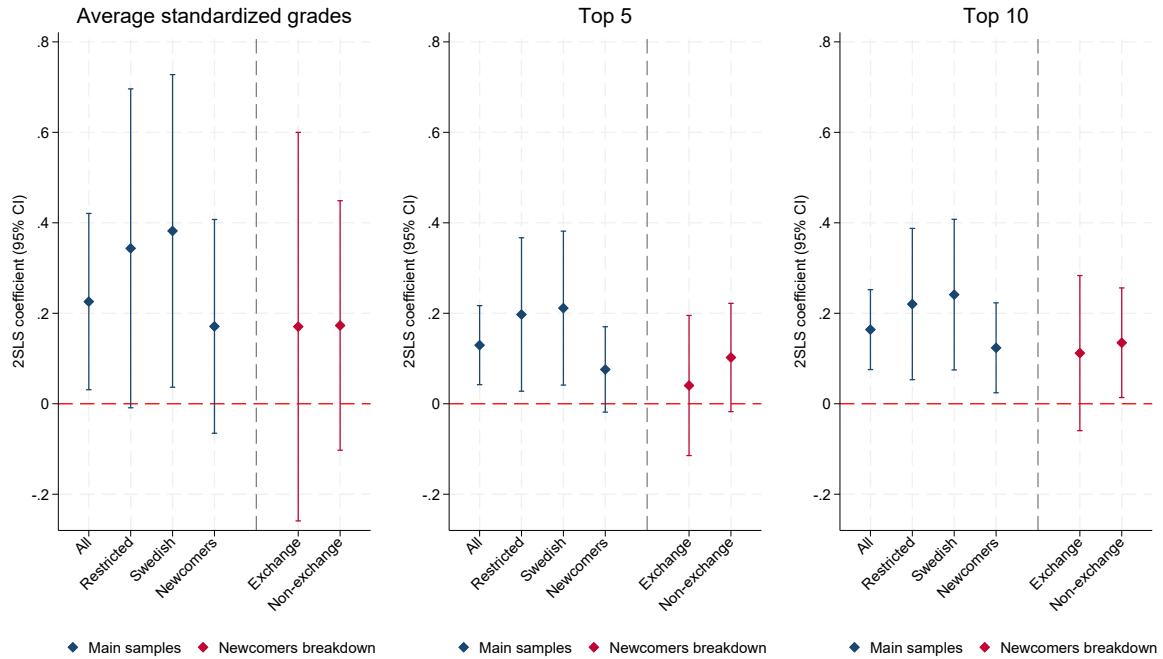
	Average standardized grades			Top 5			Top 10		
	RF (1)	OLS (2)	IV (3)	RF (4)	OLS (5)	IV (6)	RF (7)	OLS (8)	IV (9)
Panel A: All newcomers									
Lottery rank (=1 if < 200)	0.1299 (0.0896)			0.0600* (0.0354)			0.0962*** (0.0372)		
Accommodation by September		-0.0553 (0.0777)	0.1710 (0.1205)		-0.0155 (0.0296)	0.0790 (0.0482)		0.0031 (0.0323)	0.1266** (0.0508)
Mean (control group)	0.02	0.02	0.02	0.36	0.36	0.36	0.39	0.39	0.39
# of observations	891	891	891	891	891	891	891	891	891
Panel B: Exchange students only									
Lottery rank (=1 if < 200)	0.1529 (0.1949)			0.0401 (0.0703)			0.1041 (0.0768)		
Accommodation by September		-0.0692 (0.1313)	0.1705 (0.2191)		-0.0525 (0.0508)	0.0448 (0.0791)		-0.0328 (0.0564)	0.1161 (0.0875)
Mean (control group)	0.03	0.03	0.03	0.38	0.38	0.38	0.41	0.41	0.41
# of observations	344	344	344	344	344	344	344	344	344
Panel C: Non-exchange students only									
Lottery rank (=1 if < 200)	0.1207 (0.0950)			0.0727* (0.0404)			0.0954** (0.0411)		
Accommodation by September		-0.0463 (0.0943)	0.1731 (0.1407)		0.0093 (0.0354)	0.1042* (0.0611)		0.0274 (0.0378)	0.1367** (0.0619)
Mean (control group)	0.01	0.01	0.01	0.34	0.34	0.34	0.38	0.38	0.38
# of observations	547	547	547	547	547	547	547	547	547
Controls	No	No	No	No	No	No	No	No	No
Field of study FE	No	No	No	No	No	No	No	No	No

Notes: The table illustrates estimates of different student outcomes on a dummy variable for lottery rank below 200 (Reduced Form), on a dummy variable for having accommodation by September (OLS), and on the same dummy while instrumenting with lottery rank (IV). The outcomes are weighted by each course's number of credits (ETCS). Panel A consists of newcomer lottery participants for whom there has been a detailed grade registered in the first academic year. Panel B and Panel C divide Panel A into exchange and non-exchange students, respectively. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ams, the positive effects on the grades so far could reflect a change in the composition of students rather than a change in performance itself. The housing shortage is already known to affect academic outcomes on an extensive margin and students without secure housing sometimes turn down a place at university entirely for lack of somewhere to live. It is therefore worth checking whether something similar shows up here, on the extensive margin, among the lottery participants.

Figure 6 plots 2SLS estimates of four such outcomes: dropout, having passed at least

Figure 5: Early housing access effect on educational outcomes, by sample

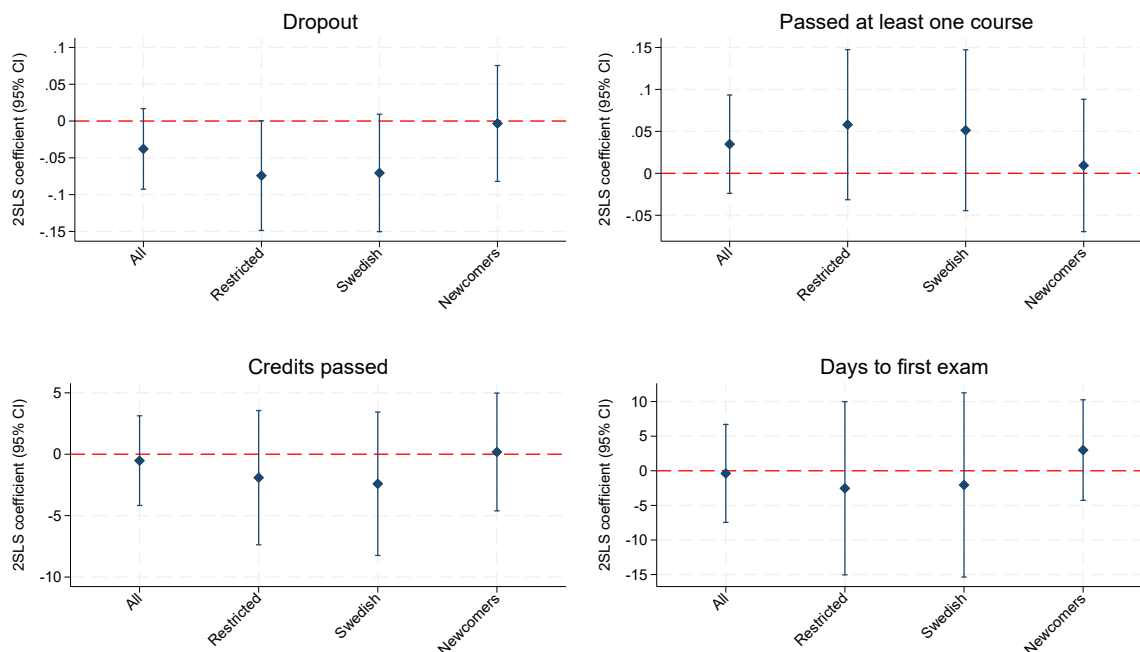


Notes: The figure above presents the coefficients and confidence intervals from the 2SLS regressions of various educational outcomes, divided into samples, on the indicator of being in student housing by September.

one course in the first year, number of total credits passed, and days to the first exam passed, for the All, Swedish, and Newcomer samples; for detailed results, see Table A4. Across nearly all specifications, the estimates are small and not statistically significant. The one exception is dropout in the Restricted and Swedish sample, where the estimate is negative and significant at the 10% level, suggesting early housing access may reduce dropout somewhat among Swedish students, though this single result should be interpreted cautiously given the number of outcomes tested. For credits passed, the estimates are close to zero and imprecise in all samples. Students with early housing access take on a similar number of credits as those without, so the grade effects reported above do not reflect differences in course load. Figure A5 illustrates this directly, plotting the distribution of credits passed separately for participants with a lottery rank below 200 and above 200. The two distributions largely overlap which is consistent with the null result in Table A4. The results also show that students without early housing do not appear to postpone their exams more than the students with it. Taken together, these results suggest that the effects on grades and rank documented above reflect a genuine improvement in performance, rather than a change in the composition

of the sample.

Figure 6: Effect of student housing receipt on enrollment and course progression, by sample



Notes: The figure presents 2SLS coefficients and 95% confidence intervals for dropout, having passed at least one course, and total credits passed, on a dummy variable for having accommodation by September, instrumenting the treatment with lottery rank ($=1$ if < 200). Estimates are shown for the All, Restricted, Swedish, and Newcomer samples. For details see Table A4.

5.2 Decomposing the effect by semester

The main results measure academic performance over the full first academic year. To see when during the year this effect actually occurs, I re-estimate Equation 1 separately for semester 1 and semester 2, using the sample of students who received at least one detailed grade, either on a percentage or A-E scale, in both semesters.²⁰ Comparing the two semesters against the full-year estimate shows whether the annual effect is driven by one part of the year or is spread evenly across both.

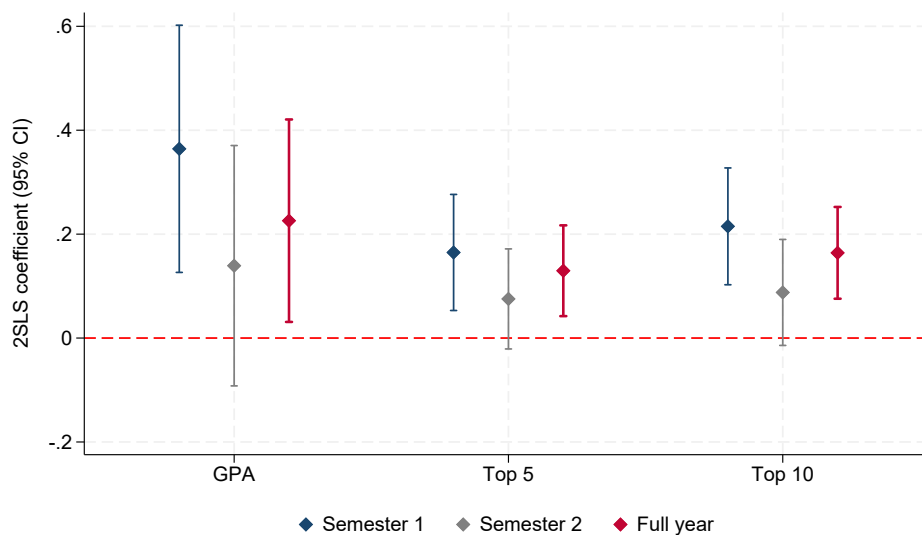
Figure 7 plots the 2SLS coefficients and confidence intervals for average grades, top 5%, and top 10%, separately for semester 1, semester 2, and the full year. Table A5 reports the corresponding estimates in detail. The pattern is consistent across all three outcomes. The effect is largest and significant in semester 1 as the average grades increase

²⁰As shown in Table A2, having a detailed grade in both semesters is not predicted by the lottery rank.

by 38% of a standard deviation, and the probability of ranking in the top 5% and top 10% increases by 43% and 49%. In semester 2, the point estimates fall substantially and the effect on average grades is no longer statistically significant.

This pattern suggests that the effect documented in the main results is concentrated in the first semester, when the gap in housing access between compliers and the rest of the sample is at its widest. By the second semester, students with worse lottery ranks have had more time to secure housing on their own, either through AF or other means, narrowing the gap and weakening the estimated effect. The full-year result remains significant nonetheless, indicating that the advantage gained in the first semester is not fully erased over the rest of the year.

Figure 7: Decomposing the effect by semester



Notes: The figure above presents the coefficients and confidence intervals from the 2SLS regressions of various educational outcomes, both for individual semesters and cumulatively for the first academic year, on the indicator of being in student housing by September. The sample includes lottery participants with detailed grades recorded in both semester 1 and semester 2.

5.3 The size of the effects

How large is an effect of 23% of a standard deviation on grades? To answer this, it is useful to compare the results of this paper with findings from other studies that examine the impacts of various interventions on educational outcomes. Marie and Zölitz (2017) find that university students' grades increase by approximately 10% of a standard deviation after being banned from entering cannabis shops. In an experiment

run by Carrell and Kurlaender (2023), they show that receiving personalized feedback from the professor increases students' grades by 9% of a standard deviation. These effects are less than half the size of the effect of having student accommodation reported in Table 5 of this study. Another study reports even smaller effects: 6% of a standard deviation increase in test scores when the student receives an additional £1,000 in student financial aid (Murphy and Wyness, 2023). The results here are more comparable in magnitude to those of Angrist et al. (2009), who find that receiving financial aid up to \$5,000 increases university students' GPA by 17.7% of a standard deviation.

Most of the other studies to which this paper relates focus on school students, not university students, largely because access to data on university grades is rare. Nonetheless, for the sake of comparison, it is useful to benchmark these results against those studies. For example, the improvement in grades observed here is nearly twice as large as the benefit of starting school one hour later, which allows high school students to be more well-rested (Carrell et al., 2011). The effect of student accommodation in the main specification is also larger than the impact of a standard deviation increase in teacher quality (Kane et al., 2008) and the prohibition of legal access to alcohol (Carrell et al., 2011).

Focusing specifically on studies that use Swedish data, which also mostly involve school students, it has been shown that an extra 10 days of school instruction raises grades by 1% of a standard deviation (Carlsson et al., 2015) and a class size reduction of seven students improves the cognitive abilities of students by 0.23 of a standard deviation (Fredriksson et al., 2013). Additionally, Sund (2009) finds that a one standard deviation increase in peer GPA leads to a 0.08 standard deviation increase in high school grades, and Cattani et al. (2023) demonstrate that increasing total absences by ten days reduces a student's GPA by 4.4% of a standard deviation. The results obtained in the current study can therefore be considered large when compared to existing literature on the determinants of grades. It cannot be ruled out, however, that the true effect is much smaller than the point estimate: taking the confidence interval into account, the effect could be as small as 3% of a standard deviation, which falls within the range reported by the studies above.

One possible explanation for a large point estimate is that the lack of accommodation

leads some students to take up employment, face long commutes, or share housing in ways that affect their academic performance. These mechanisms are examined further in Section 7.

5.4 Timing of the treatment

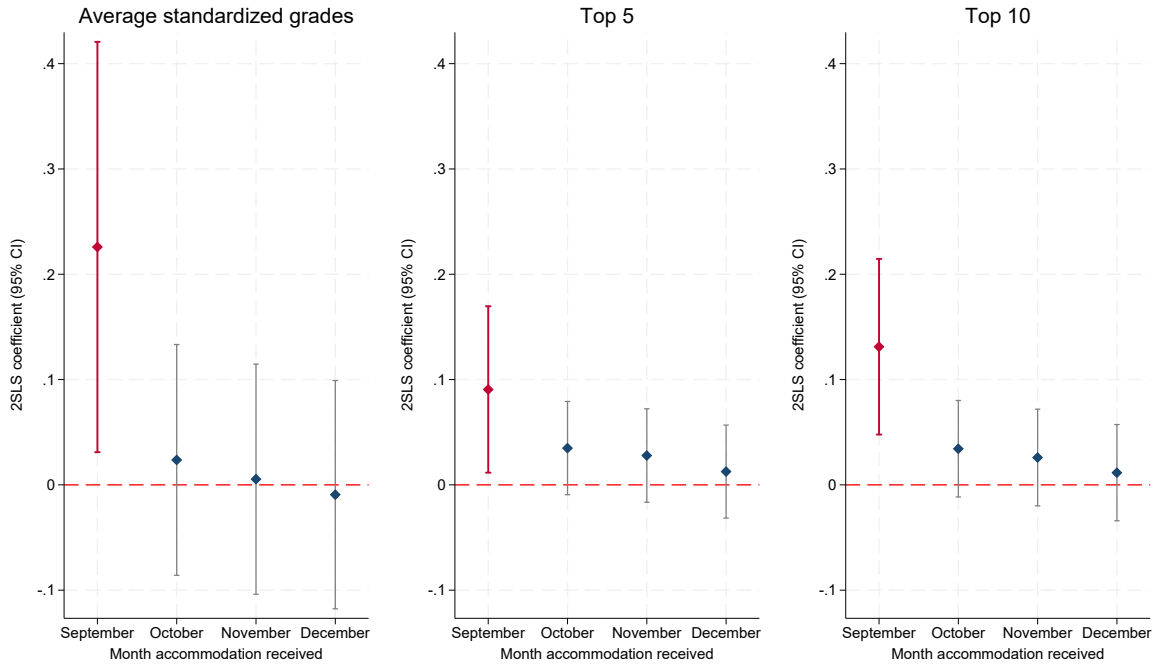
So far, the treatment has been defined as securing accommodation by September, the start of the academic year. The next step is to assess how the effects change if this window is extended further into the semester. By moving the treatment cutoff to later months, it is possible to determine whether the observed effects are specific to accommodation received by September, or whether accommodation secured later in the semester delivers similar benefits.

Figure 8 plots the results of shifting the treatment month from September to October, November, and December. Each treatment is defined as receiving accommodation by the start of the specified month or earlier; for instance, “accommodation by October” equals 1 if the participant received housing by the start of October, and 0 otherwise.²¹ Table A6 reports the corresponding estimates in detail. Since the number of units AF releases each month differs (see Table 1), the lottery rank threshold used to define the instrument also differs by month. A later cutoff month corresponds to a larger cumulative number of units, and so a higher rank threshold. The four instruments are therefore not the same instrument evaluated at different points in time. Each one identifies a different group of compliers, defined relative to that month’s own threshold. A decline in the estimated effect from one month to the next could reflect a genuine weakening of the benefit of housing received later in the semester. It could also reflect a shift toward a different complier population as the threshold widens. The results here cannot fully separate these two explanations.

With that caveat in mind, the estimates for October, November, and December are small and imprecise relative to the September estimate, for all three outcomes. One interpretation consistent with this pattern is that accommodation received after the semester has already begun does not deliver the same benefit as accommodation secured before-

²¹Note that some students may receive housing in subsequent years. However, this study only observes their first-year housing status.

Figure 8: Effects of receiving student housing in different months



Notes: These figures present the coefficients and confidence intervals from the 2SLS regressions of various educational outcomes on having accommodation across different months. The estimates are calculated using the sample of lottery participants for whom there has been a detailed grade registered in the first academic year (All sample).

hand. Students in these later treatment groups spent the initial weeks of the semester without stable housing. By the time they secure accommodation, the effects of mechanisms examined later in this paper, such as adjustments to work or living arrangements made during that unstable period, may already be in place. This would suggest that when students receive accommodation matters, not just whether they eventually receive it. Given the concern about the change in complier composition, however, this interpretation should be read as suggestive rather than conclusive.

6 Heterogeneity

Heterogeneous effects may arise based on the characteristics of the students. Some students may benefit more from access to student housing rather than relying on the private rental market. Landlords in the private market often "cherry-pick" tenants, aiming to minimize potential management issues and ensure a stable rent income. Male and minority students, in particular, face greater challenges in securing rentals in the

Table 8: Effects of student housing receipt on women vs. men

	Average standardized grades	Top 5	Top 10
Panel A: Women only			
Accommodation by September	0.1784 (0.1188)	0.0768 (0.0513)	0.0831 (0.0510)
Mean	0.04	0.34	0.38
# of observations	805	805	805
Panel B: Men only			
Accommodation by September	0.2708* (0.1571)	0.1050* (0.0617)	0.1765*** (0.0673)
Mean	0.03	0.32	0.37
# of observations	796	796	796

Notes: The table illustrates 2SLS estimates of different student outcomes on a dummy variable for having accommodation by September while instrumenting the treatment with lottery rank (=1 if ≤ 200). Panel A includes the participants who are women and panel B includes the participants who are men. The estimates are calculated using the sample of lottery participants for whom there has been a detailed grade registered in the first academic year. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

private market, as landlords are more likely to discriminate against male and ethnic renters when selecting tenants (Öblom and Antfolk, 2017; Flage, 2018).

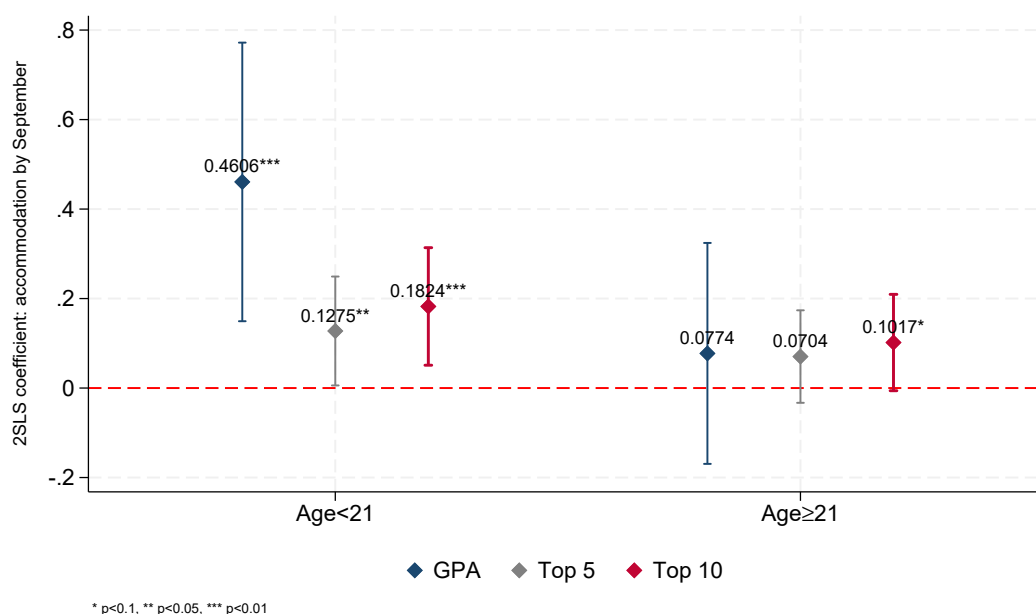
Moreover, younger adults are more often subject to discrimination in the private rental market. Studies suggest that landlords often fail to fulfill their contractual obligations when renting to younger tenants which in turn results in unsatisfactory living conditions (Lister, 2006; Mackie, 2016; Maalsen et al., 2021). This combination of biases and barriers makes student housing a potentially valuable option for these groups. While data on race is unavailable, I start by investigating gender differences in student housing benefits by dividing the sample into male and female participants. Table 8 reports the results of this heterogeneity analysis. None of the estimates are statistically significant for women, though the point estimates are positive. For men, the effects are significant across all three outcomes. This is consistent with the discrimination literature discussed above. If men face greater barriers securing housing on the private market, an allocation mechanism like AF's lottery would potentially matter more for them than for women. Unlike the private market, AF assigns priority randomly rather than through landlord discretion, and women may find it comparatively easier to secure private housing on their own.

To investigate potential differences in effects across age groups, students are divided

into two categories of participants below age 21 and participants aged 21 and above. This cutoff was chosen for two reasons. It splits the sample into two reasonably sized groups, 554 and 1,047 observations rather than an extremely uneven split. It also separates students at a meaningful point since participants below 21 are more likely to be in the earlier, junior years of a bachelor's program, while participants 21 and above are more likely to be further along in their studies or enrolled in graduate programs. Figure 9 plots the coefficients for each outcome (for detailed results, see Table A7). The most striking difference is the estimated effects on grades. Participants below 21 are significantly affected by receiving student housing, with grades increasing by 46% of a standard deviation. For participants aged 21 and above, the effects are smaller and mostly not statistically significant. Several factors could explain why younger students are more strongly affected. As mentioned earlier, there is some evidence of discrimination in the private rental market against younger tenants, which could make it harder for them to find suitable housing on their own. Another possible explanation is that younger students may be more dependent on a stable living environment during the critical period of starting higher education, while older students may have more experience and access to resources that make the timing of accommodation less important for them.²²

²²Balancing tests for the gender and age heterogeneity samples are reported in Table A8.

Figure 9: Effects of receiving student housing on different age groups



Notes: These figures present the coefficients and confidence intervals from regressions of various educational outcomes on having accommodation for different age groups. The estimates are calculated using the sample of lottery participants for whom there has been a detailed grade registered in the first academic year.

7 Mechanisms

Section 5 identifies a positive effect of having accommodation at the beginning of studies on the outcomes of lottery participants. In this section, additional outcomes that may be influenced by having student accommodation are explored, along with their implications for education. These outcomes are derived from survey responses, completed by around 34% of all lottery participants. Restricting to participants who also have a detailed grade in the first year, this share is nearly 22%.²³ Reflecting on the results from Survey I, participants identified rent and distance to faculty as the most important factors for housing. Survey II builds on this by asking about several outcomes that could possibly be shaped by these factors, described below.

One specific mechanism examined is the employment of lottery participants. Although

²³It was previously showed in Table A2 that having a lottery rank smaller than 200 increases the probability of participating in the survey by 8.2 percentage points. Since students are not aware of the goodness of their lottery rank, this relationship may arise from other factors. For instance, students with lower lottery ranks might receive accommodation earlier, indirectly leading to more stability and time to respond to surveys. Additionally, these students may benefit from earlier integration into the academic environment, which could increase their likelihood of engaging with university communications, including survey participation. For such reasons, the results on student accommodation and survey outcomes should be interpreted with some caution.

much of the literature has found negative effects of student employment on education, some studies suggest potential long-term benefits (Darolia, 2014; Neyt et al., 2019; Thies, 2023). The mixed results in the literature likely reflect a trade-off. Employment can reduce the time available for study. A job that is relevant to a student's field may offset this cost by building skills or experience, while an unrelated job offers little in return. Whether the net effect is positive or negative therefore depends on how well the job aligns with a student's studies, on their socioeconomic background, and on how many hours they work. A second set of outcomes concerns where and with whom students live. I investigate the location of students' residences and their living arrangements. Proximity to campus can influence class attendance and, consequently, academic performance. Having a roommate, especially a fellow student, can also impact educational outcomes depending on the roommate's academic abilities (Sacerdote, 2001; Zimmerman, 2003). I also examine the frequency of students' social interactions with friends which speaks to how they allocate time between studying and socializing, and to their broader social integration.

I re-estimate Equation 1 incorporating these new outcomes—employment, location, having a roommate, and the number of social interactions—into the analysis. I also estimate the effects on educational outcomes for this sample to show how the results compare to those from the main sample. The results of this specification are presented in Table 9, which shows the results across different samples of lottery participants.²⁴ Columns (1) and (2) show the effect on full-time and part-time employment, respectively. Overall, having a full-time job is rare among the participants with only 1%-4% of them reporting that they are employed. The effects on full-time employment are negative and significant in most samples, ranging from 2.4 to 6 percentage points in magnitude. The coefficients for part-time employment are insignificant across all panels. As mentioned, renting accommodation in the private market can put greater financial pressure on students, as these rentals are generally more expensive than those provided by AF. As a result, students may need to seek employment alongside their studies to cover the higher rent costs. This can partly explain the negative effect of having student accommodation by September on the probability of being employed full-time.

²⁴Balancing tests for these samples are reported in Table A9.

Across all samples, being in student housing increases the likelihood of living in the city where the campus is located. This is expected since all student housing units are located in the city of Lund. The effects are significant, with student accommodation increasing the probability of living in Lund by 14% to 17%, depending on the sample. Due to potential lack of housing in the city, students might resort to living in the neighboring cities. Moreover, the probability of having a roommate is negatively affected. Being in student housing decreases the probability of having a roommate by 27 percentage points for the sample of all respondents, equivalent to almost a 38% reduction. Since rental options on the private market are typically more expensive, students who rent privately often share apartments with roommates to help reduce the cost of rent. Student housing typically offers more affordable single-occupancy units that allows the students to avoid the need for roommates. This may provide greater personal space and stability and can contribute to improved educational outcomes. Columns (6) and (7) examine whether the main effects on educational outcomes are still present in the sample of survey respondents. Overall, the point estimates in Panel A and D are consistent with the effects found in Section 5. However, the estimates for Panel C and D are smaller and imprecise probably due to the lack of statistical power and small sample sizes.

The results still hold after adjusting the p-values using the Benjamini-Hochberg multiple hypothesis testing method. The adjusted and raw p-values for the regressions in Panel A of Table 9 are presented in Table A10.

7.1 Housing stability index

Stability in the living situation was previously discussed as a potential mechanism through which student accommodation can affect education. To establish this link, I employed the same 2SLS analysis using a housing stability index as the outcome. This index was constructed using two factors:

Duration of stay: This factor measures how long students can stay in their current housing. Students in AF apartments can remain in their units until the end of their studies, provided that it does not exceed six years. In contrast, private market rentals may have shorter lease periods, sometimes as short as three months. Such short-term

Table 9: Potential mechanisms

	(1) Full-time employment	(2) Part-time employment	(3) Living in Lund	(4) Having roommate	(5) Social activities (per week)	(6) Standardized grades	(7) Top 10
Panel A: All respondents							
Accommodation by September	-0.0473*** (0.0124)	-0.0198 (0.0929)	0.1615*** (0.0353)	-0.2662** (0.1290)	1.0488 (0.7225)	0.2091 (0.1496)	0.0928 (0.0644)
Mean (control group)	0.03	0.15	0.87	0.68	3.74	0.01	0.37
# of observations	1,021	1,021	1,021	1,021	1,021	1,021	1,021
# of observations (unique)	560	560	560	560	560	560	560
Panel B: Restricted sample respondents							
Accommodation by September	-0.0238* (0.0135)	-0.0528 (0.1574)	0.1317*** (0.0390)	-0.3528* (0.2084)	0.8602 (1.0207)	0.1438 (0.2390)	0.0256 (0.1200)
Mean (control group)	0.01	0.13	0.92	0.60	3.88	0.01	0.34
# of observations	412	412	412	412	412	412	412
# of observations (unique)	241	241	241	241	241	241	241
Panel C: Swedish respondents							
Accommodation by September	-0.0247* (0.0142)	-0.0553 (0.1649)	0.1356*** (0.0419)	-0.3993* (0.2159)	0.7368 (1.0739)	0.1596 (0.2494)	0.0399 (0.1249)
Mean (control group)	0.01	0.13	0.93	0.61	3.90	0.02	0.35
# of observations	392	392	392	392	392	392	392
# of observations (unique)	229	229	229	229	229	229	229
Panel D: Newcomer respondents							
Accommodation by September	-0.0604*** (0.0173)	0.0198 (0.1181)	0.1706*** (0.0483)	-0.1909 (0.1586)	1.0444 (1.0274)	0.2073 (0.1950)	0.1293* (0.0715)
Mean (control group)	0.04	0.16	0.84	0.74	3.64	0.01	0.39
# of observations	594	594	594	594	594	594	594
# of observations (unique)	310	310	310	310	310	310	310
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table illustrates estimates of different student outcomes on an indicator for having accommodation by September while instrumenting the treatment with lottery rank (2SLS). The table has been divided into four panels: Panel A consists of all of the lottery participants who responded to the survey. Panel B is the sample of the respondents with complete demographic data available. Panel C includes only Swedish respondents with complete demographic data available. Panel D involves a sample of the respondents with no demographic data available. The students in all panels have at least one detailed grade registered in the first academic year. Survey fixed effects are included. Standard errors are clustered at individual level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

leases can increase housing instability and force students to move during their studies, potentially harming their educational outcomes due to the stress of finding new accommodation and moving. For this variable, each survey respondent is assigned a score between 1 (less than a month) and 4 (entire study period), with 4 indicating the

highest stability.

Type of rental contract: This factor assesses the type of rental contract students have. All AF units are first-hand contracts, with leases signed directly between tenants and AF. This provides legal protections, such as regulated rents. Many private market rentals may involve second-hand contracts or no legal contracts at all, both of which offer less stability compared to a first-hand contract.²⁵ This variable is scored between 1 (no legal contract) and 5 (owning an apartment), with 5 representing the most stable option.

A principal component analysis (PCA) suggests that the two measures capture a common dimension of housing security. The first component explains 62% of the variation and places nearly equal weight on both measures. As a result, it is equivalent to their standardized sum. The survey also records the notice period at a student's current residence. This measure is excluded from the index because the PCA suggests that it does not capture the same underlying dimension of housing security. Table 10 presents the effects of receiving student housing early on the housing stability index. The estimated effects are 0.57 and 0.91 standard deviations, depending on the specification. Greater housing stability, in turn, may contribute to improved educational outcomes for these students.

Table 10: Effects of student housing receipt on housing stability

	(1) Housing stability index	(2) Housing stability index
Accommodation by September	0.9107*** (0.1259)	0.5715*** (0.1526)
Mean (control group)	-0.10	-0.10
# of observations	1,446	1,446
Survey FE	Yes	Yes
Field of study FE	No	Yes

Notes: The table illustrates estimates of the housing stability index on an indicator for having accommodation by September while instrumenting the treatment with lottery rank (2SLS). The index is created as explained in section 7.1. Standard errors are clustered at individual level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

²⁵Second-hand contracts, also known as sublet agreements, are rental agreements where the original tenant (primary tenant) rents out part or all of the rented premises to another person (subtenant).

8 Robustness

8.1 Binary versus continuous instrument

The main specification uses a binary instrument, $q_i < 200$, rather than the continuous lottery rank q_i itself. This choice is not arbitrary and is based on the institutional context of the lottery. As shown in Table 1, AF Bostäder made approximately 213 units available to lottery participants before the start of the semester. Therefore, a rank at or below approximately 200 is a meaningful proxy for actually receiving a housing offer under the supply conditions. As a sanity check, I let the threshold vary slightly, using $q_i < 190$, $q_i < 213$, and $q_i < 220$ instead of $q_i < 200$ (Table A11). Signs and significance are stable across all three samples and thresholds for grades and top 10.

Still, it is natural to ask whether the continuous lottery rank would work just as well. Table A12 reports the first-stage, reduced form, and 2SLS estimates when q_i is used directly. The first-stage is highly significant across all threshold definitions. The coefficient is small by construction because rank spans roughly 2,500 positions, so moving one place down the queue changes the probability of receiving accommodation by only a fraction of a percentage point. This alone is not a concern. More importantly, however, the relationship between rank and accommodation is nonlinear. Figure 3 shows that the probability of accommodation falls steeply over the first few hundred positions and then flattens into a long tail. A linear specification averages this pattern into a single slope and therefore, understates the true drop near the threshold and overstates it everywhere else, especially toward the end of the tail. For that reason, the binary instrument based on the supply provides a more meaningful representation of how queue rank translates into access to accommodation and is interpretable as the effect of receiving accommodation by September.

A quadratic term doesn't fix the nonlinearity issue either, since a parabola still isn't the right shape. A better match is a set of rank-bin dummies that are built narrow close to $q_i = 200$ and wide further. This lets the first-stage follow the data structure. Table A13 shows the underlying first-stage bin coefficients. Relative to rank 0-100, being ranked 100-200 already lowers the probability of accommodation by 26 percentage points. The same pattern continues as rank worsens and each bin lowers the probability further,

then the line becomes flat. This matches the shape of Figure 3.

Table A14 reports the 2SLS estimates using the rank bins as multiple instruments. The estimates remain positive and consistent with the main results but are generally smaller, particularly for grades in the full sample and the newcomer subsample, where they are no longer statistically significant. The results for the Swedish sample line up with the main specification and remain significant across all three outcomes. The loss of significance for the other samples can be explained by the fact that several of the bins are located in the flat part of the rank distribution, where accommodation probability barely moves at all. These bins add little real information, but they still add noise, so adding them into the same estimate makes it less precise.

Because the rank-bin specification uses multiple instruments, I also report the Hansen J test. The test is passed for all outcomes in the Swedish sample and for grades in the All sample, but not for the remaining outcomes. This suggests that treatment effects may vary across the rank distribution in some samples. This does not affect the main results, which rely on a local comparison around $q_i = 200$.

8.2 Comparison group and bandwidth sensitivity

The AF Bostäder lottery assigns every participant a queue position and no participant is excluded from the housing queue or fails to receive a rank. There are no *losers* in this lottery in that sense, since *every* participant remains eligible to receive AF housing, and a worse lottery rank implies a longer expected wait rather than disqualification. This point is emphasized here because it is directly relevant to how the comparison group in this analysis should be understood.

Treatment in this analysis is defined narrowly. A lottery participant is treated if they received AF housing before the start of the academic year, by September 2022. The comparison group consists of all lottery participants who had not received housing by that date. Given the queue-based nature of the access, this group simply had not yet reached the front of the queue by the start of the semester. This comparison is well-defined at a single point in time and does not depend on what happens afterwards. It is then informative to describe what happens to the comparison group in the remain-

der of the observation window until May 2023. Consistent with the queue mechanism, participants continue to move through the queue and receive housing throughout the year. Some go on to receive AF housing later in the academic year, while others still have not received housing by the end of the observation period, either because their queue priority is still too low, because housing has been secured through other means, or for reasons not observed in the data. Subsequent housing status may therefore depend on factors other than the lottery rank.

Figure A6 plots three probabilities against continuous lottery rank: being housed by September, getting housing later but by May, and not yet having housing by May. As already shown, the probability of being housed by September falls consistently as rank worsens. Among the remaining two outcomes, getting housing later is more common at moderate ranks, while not yet having housing becomes more common as rank continues to worsen. This fits the queue mechanism well. Participants with a poor rank have simply not yet reached the front of the queue within the observation window. Given more time, they remain eligible to receive housing like everyone else.

This motivates a natural robustness check. The instrument identifies a local average treatment effect around the $q_i = 200$ threshold, and this local interpretation is most credible when the comparison is not stretched across participants with very different lottery outcomes. As Figure A6 shows, the comparison group becomes increasingly weighted toward participants still waiting in the queue as q_i grows, so it is useful to check whether the main results hold up when this comparison is kept closer to the threshold. The main specification is therefore re-estimated on subsamples restricted to participants with $q_i \leq 1500$, $q_i \leq 1000$, and $q_i \leq 700$, in addition to the full sample, while using the $q_i < 200$ instrument throughout. The cutoffs follow Figure A6. At $q_i \leq 700$, more participants have been housed since September than are still waiting. At $q_i \leq 1000$, these two groups are about equal in size. At $q_i \leq 1500$, the group still waiting has become somewhat larger.

Table A15 reports the results, separately for the All, Swedish, and Newcomer samples. The point estimates are stable across bandwidths and remain statistically significant in most cases, with standard errors widening as expected given the shrinking sample size. The Newcomer sample shows weaker effects throughout, including in the full

sample, so the bandwidth restriction changes little there. Overall, the estimates are not concentrated among participants far from the $q_i = 200$ threshold, which reinforces the main specification.

9 Conclusion

Housing shortages have become a persistent problem in many university towns, yet the consequences of this instability for students' academic performance and labor supply remain largely unknown. This paper studies whether the timing of access to student housing affects both. I use a student housing lottery in Sweden, which randomly assigns queue priority to newly admitted students, to identify the causal effect of receiving affordable housing at the start of the academic year, rather than later.

The results show that early access to student housing has a significant positive effect on academic outcomes. Students who secure accommodation by the start of the semester achieve higher grades and are more likely to rank among the top students in their courses. This effect is strongest in the first semester, and getting housing later in the year does not lead to the same benefits. Timing, not just eventual access, is what matters. The effect also varies across groups and is more pronounced for male and younger students. I find no effect on extensive-margin outcomes such as dropping out and degree progression. This suggests the results reflect a genuine improvement in academic performance, rather than a shift in the composition of the sample. To shed light on why early access to affordable housing matters, I run a survey among lottery participants and use it to explore potential mechanisms. Early access to housing reduces full-time employment during studies by 2 to 6 percentage points. The evidence also points to housing stability and living location and arrangements as channels linking early access to academic performance.

These findings suggest that the difficulty many students face in finding housing at the start of their studies is not only an inconvenience, but a real barrier to academic performance. As universities and cities continue to face housing shortages, expanding access to stable, affordable, and timely accommodation may be an effective way to improve student outcomes. A natural next step is to better understand which of the mechanisms

explored here matter most and whether interventions that speed up access to housing, rather than simply expanding its supply, can meaningfully improve outcomes for the students who need it most.

References

- Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics*, 113(2), 231–263.
- Albouy, D., Ehrlich, G., & Liu, Y. (2016). Housing demand, cost-of-living inequality, and the affordability crisis. *National Bureau of Economic Research*, (22816).
- Altonji, J. G., & Zhong, L. (2021). The labor market returns to advanced degrees. *Journal of Labor Economics*, 39(2), 303–360.
- Angrist, J., Lang, D., & Oreopoulos, P. (2009). Incentives and services for college achievement: Evidence from a randomized trial. *American Economic Journal: Applied Economics*, 1(1), 136–163.
- Angrist, J., Oreopoulos, P., & Williams, T. (2014). When opportunity knocks, who answers?: New evidence on college achievement awards. *Journal of Human Resources*, 49(3), 572–610.
- Azmat, G., Bagues, M., Cabrales, A., & Iriberry, N. (2019). What you don't know... can't hurt you? a natural field experiment on relative performance feedback in higher education. *Management Science*, 65(8), 3714–3736.
- Baert, S., Marx, I., Neyt, B., Van Belle, E., & Van Casteren, J. (2018). Student employment and academic performance: An empirical exploration of the primary orientation theory. *Applied Economics Letters*, 25(8), 547–552.
- Bettinger, E., & Long, B. T. (2010). Does cheaper mean better? the impact of using adjunct instructors on student outcomes. *The Review of Economics and Statistics*, 92(3), 598–613.
- Braxton, J., & Hirschy, A. (2005). Theoretical developments in the study of college student departure. *College student retention: Formula for student success*, 3, 61–87.
- Broton, K., & Goldrick-Rab, S. (2018). Going without: An exploration of food and housing insecurity among undergraduates. *Educational Researcher*, 47(2), 121–133.

- Broton, K., Mohebbi, M., & Lingo, M. D. (2022). Basic needs insecurity and mental health: Community college students' dual challenges and use of social support. *Community College Review*, 50(4), 456–482.
- Bütikofer, A., Mølland, E., & Salvanes, K. G. (2018). Childhood nutrition and labor market outcomes: Evidence from a school breakfast program. *Journal of Public Economics*, 168, 62–80.
- Callender, C. (2008). The impact of term-time employment on higher education students' academic attainment and achievement. *Journal of education policy*, 23(4), 359–377.
- Card, D. (1995). Using geographic variation in college proximity to estimate the return to schooling. *Aspects of Labour Market Behavior: Essays in Honour of John Vanderkamp*. Ed. L.N. Christophides, E.K. Grant, and R. Swidinsky, 201–222.
- Card, D. (1999). The causal effect of education on earnings. *Handbook of labor economics*, 3, 1801–1863.
- Carlsson, M., Dahl, G. B., Öckert, B., & Rooth, D.-O. (2015). The effect of schooling on cognitive skills. *Review of Economics and statistics*, 97(3), 533–547.
- Carrell, S., & Kurlaender, M. (2023). My professor cares: Experimental evidence on the role of faculty engagement. *American Economic Journal: Economic Policy*, 15(4), 113–141.
- Carrell, S., Maghakian, T., & West, J. E. (2011). A's from zzzz's? the causal effect of school start time on the academic achievement of adolescents. *American Economic Journal: Economic Policy*, 3(3), 62–81.
- Cattan, S., Kamhöfer, D. A., Karlsson, M., & Nilsson, T. (2023). The long-term effects of student absence: Evidence from sweden. *The Economic Journal*, 133(650), 888–903.
- Chetty, R., Hendren, N., & Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4), 855–902.
- Currie, J. (1994). Welfare and the well-being of children: The relative effectiveness of cash and in-kind transfers. *Tax policy and the economy*, 8, 1–43.

- Darolia, R. (2014). Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and part-time students. *Economics of Education Review*, 38, 38–50.
- Dustmann, C., Fitzenberger, B., & Zimmermann, M. (2022). Housing expenditure and income inequality. *The Economic Journal*, 132(645), 1709–1736.
- Dynarski, S. M. (2003). Does aid matter? measuring the effect of student aid on college attendance and completion. *American Economic Review*, 93(1), 279–288.
- Flage, A. (2018). Ethnic and gender discrimination in the rental housing market: Evidence from a meta-analysis of correspondence tests, 2006–2017. *Journal of Housing Economics*, 41, 251–273.
- Fredriksson, P., Öckert, B., & Oosterbeek, H. (2013). Long-term effects of class size. *The Quarterly journal of economics*, 128(1), 249–285.
- Freier, R., Schumann, M., & Siedler, T. (2015). The earnings returns to graduating with honors—evidence from law graduates. *Labour Economics*, 34, 39–50.
- Fricke, H. (2018). Tuition fees, student finances, and student achievement: Evidence from a differential raise in fees. *Journal of Human Capital*, 12(3), 504–541.
- Glaeser, E., & Gyourko, J. (2018). The economic implications of housing supply. *Journal of economic perspectives*, 32(1), 3–30.
- Goldrick-Rab, S., Richardson, J., & Hernandez, A. (2017). Hungry and homeless in college: Results from a national study of basic needs insecurity in higher education.
- Hallett, R. E., & Freas, A. (2018). Community college students' experiences with homelessness and housing insecurity. *Community College Journal of Research and Practice*, 42(10), 724–739.
- Hsieh, C.-T., & Moretti, E. (2019). Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics*, 11(2), 1–39.
- Jacob, B. A., Kapustin, M., & Ludwig, J. (2015). The impact of housing assistance on child outcomes: Evidence from a randomized housing lottery. *The Quarterly Journal of Economics*, 130(1), 465–506.
- Kalenkoski, C. M., & Pabilonia, S. W. (2010). Parental transfers, student achievement, and the labor supply of college students. *Journal of Population Economics*, 23, 469–496.

- Kane, T. J., Rockoff, J. E., & Staiger, D. O. (2008). What does certification tell us about teacher effectiveness? evidence from new york city. *Economics of Education review*, 27(6), 615–631.
- Kirkeboen, L. J., Leuven, E., & Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3), 1057–1111.
- Kobus, M. B., Van Ommeren, J. N., & Rietveld, P. (2015). Student commute time, university presence and academic achievement. *Regional Science and Urban Economics*, 52, 129–140.
- Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the effects of student engagement on first-year college grades and persistence. *The journal of higher education*, 79(5), 540–563.
- Kumar, T. (2021). The housing quality, income, and human capital effects of subsidized homes in urban india. *Journal of Development Economics*, 153, 102738.
- Lister, D. (2006). Unlawful or just awful? young people’s experiences of living in the private rented sector in england. *Young*, 14(2), 141–155.
- Lundborg, P., Rooth, D.-O., & Alex-Petersen, J. (2022). Long-term effects of childhood nutrition: Evidence from a school lunch reform. *The Review of Economic Studies*, 89(2), 876–908.
- Maalsen, S., Wolifson, P., Rogers, D., Nelson, J., & Buckle, C. (2021). Understanding discrimination effects in private rental housing. *AHURI Final Report*.
- Mackie, P. K. (2016). Young people and housing: Identifying the key issues.
- Marbach, M., & Hangartner, D. (2020). Profiling compliers and noncompliers for instrumental-variable analysis. *Political Analysis*, 28(3), 435–444.
- Marie, O., & Zölitz, U. (2017). “high” achievers? cannabis access and academic performance. *The Review of Economic Studies*, 84(3), 1210–1237.
- Murphy, M., Gopalan, M., Carter, E., Emerson, K. T., Bottoms, B. L., & Walton, G. M. (2020). A customized belonging intervention improves retention of socially disadvantaged students at a broad-access university. *Science Advances*, 6(29), eaba4677.
- Murphy, R., & Wyness, G. (2023). Testing means-tested aid. *Journal of Labor Economics*, 41(3), 687–727.

- Neyt, B., Omeij, E., Verhaest, D., & Baert, S. (2019). Does student work really affect educational outcomes? a review of the literature. *Journal of economic surveys*, 33(3), 896–921.
- Nonis, S. A., & Hudson, G. I. (2006). Academic performance of college students: Influence of time spent studying and working. *Journal of education for business*, 81(3), 151–159.
- Öblom, A., & Antfolk, J. (2017). Ethnic and gender discrimination in the private rental housing market in finland: A field experiment. *PloS one*, 12(8), e0183344.
- Oreopoulos, P., & Petronijevic, U. (2019). *The remarkable unresponsiveness of college students to nudging and what we can learn from it* (tech. rep.). National Bureau of Economic Research.
- Öst, C. E., & Johansson, P. (2023). The consequences of the swedish rent control system on labor income: Evidence from a randomized apartment lottery. *Journal of Public Economics*, 221, 104864.
- QS World University Rankings. (2024). <https://www.topuniversities.com/world-university-rankings/2024?countries=se>
- Reynolds, C. L. (2020). The effect of dormitory residence during college on student outcomes. *Journal of Human Capital*, 14(2), 249–289.
- Riksdagen. (2022). Motion 2022/23:1339 – Student Housing Situation [[Accessed: YYYY-MM-DD]]. https://www.riksdagen.se/sv/dokument-och-lagar/dokument/motion/utred-studentbostadssituationen_HA021339
- Rothstein, D. S. (2007). High school employment and youths’ academic achievement. *Journal of Human Resources*, 42(1), 194–213.
- Sacerdote, B. (2001). Peer effects with random assignment: Results for dartmouth roommates. *The Quarterly journal of economics*, 116(2), 681–704.
- SFS. (2024). Bostadsrapport. <https://sfs.se/har-ar-sfs-bostadsrapport-2024/>
- Silva, M. R., Kleinert, W. L., Sheppard, A. V., Cantrell, K. A., Freeman-Coppadge, D. J., Tsoy, E., Roberts, T., & Pearrow, M. (2017). The relationship between food security, housing stability, and school performance among college students in an urban university. *Journal of College Student Retention: Research, Theory & Practice*, 19(3), 284–299.

- Statistics Sweden. (2023). Flergenerationsregistret, Registret över totalbefolkningen, Högskoleregistret, 2021-2022.
- Stinebrickner, R., & Stinebrickner, T. R. (2003). Working during school and academic performance. *Journal of Labor Economics*, 21(2), 473–491.
- Sund, K. (2009). Estimating peer effects in Swedish high school using school, teacher, and student fixed effects. *Economics of Education Review*, 28(3), 329–336.
- Sveriges Radio. (2024). Var fjärde student avböjer studier på grund av bostadsbrist [[Accessed: YYYY-MM-DD]]. <https://www.sverigesradio.se/artikel/var-fjarde-student-avbojer-studier-pa-grund-av-bostadsbrist>
- Swedish Higher Education Authority. (2023). Annual status report. <https://www.uka.se/swedish-higher-education-authority/our-results/annual-status-report>
- The Guardian. (2023). Student housing used to be affordable. why has it become an ‘asset class’ to enrich the already wealthy? <https://www.theguardian.com/commentisfree/2023/aug/30/student-accommodation-university-housing-crisis>
- Thies, T. (2023). International students in higher education: The effect of student employment on academic performance and study progress. *Higher Education*, 86(4), 933–951.
- Turk, J. M., & González Canché, M. S. (2019). On-campus housing’s impact on degree completion and upward transfer in the community college sector: A comprehensive quasi-experimental analysis. *The Journal of Higher Education*, 90(2), 244–271.
- UN Habitat. (2015). Housing at the center of the new urban agenda.
- Van Dijk, W. (2019). The socio-economic consequences of housing assistance. *University of Chicago Kenneth C. Griffin Department of Economics job market paper*, 0–46 i–xi, 36.
- Walton, G. M., & Cohen, G. L. (2011). A brief social-belonging intervention improves academic and health outcomes of minority students. *Science*, 331(6023), 1447–1451.
- Wenz, M., & Yu, W.-C. (2010). Term-time employment and the academic performance of undergraduates. *Journal of Education Finance*, 358–373.

- Zhang, L. (2008). The way to wealth and the way to leisure: The impact of college education on graduates' earnings and hours of work. *Research in Higher Education*, 49, 199–213.
- Zimmerman, D. J. (2003). Peer effects in academic outcomes: Evidence from a natural experiment. *Review of Economics and statistics*, 85(1), 9–23.

Appendices

A Tables

Table A1: Grade conversion

Grade	Percentage Range	Mean Percentage
A	85–100	92.5
B	75–84	79.5
C	65–74	69.5
D	55–64	59.5
E	50–54	52.0

Notes: The table above shows the grade conversion from the A-E grading scale to percentage ranges and the corresponding mean.

Table A2: Differential attrition: lottery rank and sample appearance

	(1) 1 st semester sample	(2) 2 nd semester sample	(3) 1 st year sample	(4) Survey sample
Lottery rank (=1 if < 200)	0.0230 (0.0361)	-0.0103 (0.0368)	-0.0062 (0.0358)	0.0818** (0.0363)
Mean	0.59	0.55	0.63	0.34
# of observations	2,546	2,546	2,546	2,546

Notes: The table presents linear probability model estimates of the relationship between lottery rank (=1 if < 200) and the likelihood of appearing in each analysis sample. The semester 1, semester 2, and full-year samples require a detailed grade to be available for that period. The survey sample consists of lottery participants who responded to Survey II. Robust standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

Table A3: Random assignment test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Age	Female	Foreign background	Graduate	Study grant, $t - 1$	Employment, $t - 1$	Annual income, $t - 1$	Mother's income	Father's income	Mother's education	Father's education
Dependent variable											
	Panel A: Restricted sample										
Lottery rank (=1 if < 200)	-0.3617** (0.1778)	-0.0496 (0.0715)	0.0177 (0.0340)	-0.0352 (0.0216)	0.0802 (0.0512)	-0.0240 (0.0713)	-112.7702 (122.6433)	-340.6063 (471.9670)	-1,489.1154** (679.4686)	0.0885 (0.1063)	0.0649 (0.1686)
Mean	19.63	0.44	0.04	0.05	0.79	0.63	990.03	6,008.68	8,160.67	4.64	4.59
# of observations	635	635	635	635	635	635	635	635	635	635	635
Joint F-statistic						0.96					
Prob>F						0.49					
	Panel B: Survey respondents										
Lottery rank (=1 if < 200)	-0.3429 (0.2687)	-0.0286 (0.1138)	0.0000 (0.0490)	-0.0333*** (0.0124)	0.0714 (0.0913)	0.0048 (0.1138)	-97.1000 (256.7098)	-330.1143 (602.3335)	-1,767.2667* (1,045.9972)	-0.1143 (0.1829)	0.3190 (0.3121)
Mean	19.69	0.45	0.05	0.03	0.74	0.57	1,068.13	5,525.96	7,531.70	4.63	4.57
# of observations	231	231	231	231	231	231	231	231	231	231	231
Joint F-statistic						1.46					
Prob>F						0.15					
	Panel C: Survey non-respondents										
Lottery rank (=1 if < 200)	-0.3843 (0.2379)	-0.0665 (0.0919)	0.0292 (0.0467)	-0.0335 (0.0353)	0.0925 (0.0586)	-0.0351 (0.0915)	-134.5250 (106.2734)	-281.4602 (673.0473)	-1,212.9824 (858.5254)	0.2303* (0.1215)	-0.1070 (0.1819)
Mean	19.59	0.43	0.04	0.06	0.81	0.67	945.37	6,284.69	8,520.31	4.65	4.60
# of observations	404	404	404	404	404	404	404	404	404	404	404
Joint F-statistic						0.88					
Prob>F						0.56					

Notes: The table shows separate OLS estimates for lottery rank indicator on pre-determined characteristics of the participants. Panel A uses the sample of all participants with control variables available, and the sample gets divided into two groups of survey respondents and non-respondents in panel B and panel C, respectively. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effect of student housing receipt on enrollment and course progression

Dependent Variable	(1) All	(2) Swedish	(3) Newcomers
Dropout	-0.0378 (0.0279)	-0.0705* (0.0407)	-0.0033 (0.0402)
Mean (control group)	0.09	0.08	0.09
# of observations	2,546	1,188	1,240
Passed at least one course	0.0348 (0.0299)	0.0513 (0.0489)	0.0093 (0.0402)
Mean (control group)	0.91	0.91	0.91
# of observations	2,546	1,188	1,240
Credits passed	1.5587 (2.2089)	3.6512 (2.5705)	0.1848 (2.6861)
Mean (control group)	49.20	55.00	44.67
# of observations	1,601	608	891
Days to first exam	-1.0672 (3.0293)	-4.1229 (4.0146)	0.7582 (3.8455)
Mean (control group)	39.70	31.65	45.83
# of observations	1,601	608	891

Notes: The table illustrates 2SLS estimates of dropout, having passed at least one course, total credits passed (ECTS, any field, first year), and days to the first exam taken, on a dummy variable for having accommodation by September, instrumenting the treatment with lottery rank. Dropout and passed-at-least-one-course use the extensive sample available for each outcome, with no grade-completeness restriction. Credits passed and days to the first exam are restricted to the subsample that also has standardized grades, top 5, and top 10 available. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Decomposing the effect (Semester 1 versus semester 2)

Dependent Variable	(1) 1 st Semester	(2) 2 nd Semester	(3) 1 st Year
Average Standardized Grades	0.3815*** (0.1347)	0.1784 (0.1157)	0.2625** (0.1029)
Mean	0.04	0.07	0.06
Top 5	0.1388** (0.0608)	0.0940* (0.0504)	0.1001** (0.0429)
Mean	0.32	0.31	0.33
Top 10	0.1812*** (0.0622)	0.1083** (0.0538)	0.1255*** (0.0444)
Mean	0.37	0.35	0.38
# of observations	1,299	1,299	1,299

Notes: This table presents the results of the 2SLS regressions of educational outcomes on the indicator of having student accommodation by September, using lottery rank as IV. The results are presented separately for semester 1, semester 2, and the first year cumulatively. The sample of students with grades available in both semesters is used. Dependent variables are listed in the rows. The treatment is having accommodation at the start of the academic year by the beginning of September. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effects of student housing receipt at different times on educational outcomes

	(1) Average standardized grades	(2) Top 5	(3) Top 10	(4) N	(5) N (Control)	(6) Weak IV test F-stat	(7) Instrument
Accommodation by September	0.2259** (0.0994)	0.0906** (0.0403)	0.1312*** (0.0425)	1,601	1,461	248.06	Lottery rank (=1 if < 200)
Accommodation by October	0.0237 (0.0559)	0.0349 (0.0226)	0.0343 (0.0234)	1,601	1,130	1071.39	Lottery rank (=1 if < 700)
Accommodation by November	0.0054 (0.0558)	0.0279 (0.0226)	0.0260 (0.0234)	1,601	1,069	1022.97	Lottery rank (=1 if < 800)
Accommodation by December	-0.0093 (0.0553)	0.0126 (0.0225)	0.0116 (0.0233)	1,601	1,037	1013.07	Lottery rank (=1 if < 850)

Notes: The table illustrates separate 2SLS estimates of different student outcomes on a dummy variable for having accommodation by a certain month, while instrumenting the treatment with different instruments as explained in section 8. The estimates are calculated using the sample of all lottery participants for whom there has been a detailed grade registered in the first year. The outcomes are weighted by each course's number of credits (ETCS). The reported F-statistics are Montiel Olea-Pflueger's effective F-statistics for testing instrument strength. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effects of student housing receipt by age group

	Average standardized grades	Top 5	Top 10
Panel A: Age below 21			
Accommodation by September	0.4606*** (0.1588)	0.1275** (0.0621)	0.1824*** (0.0670)
Mean	0.02	0.31	0.35
# of observations	554	554	554
Panel B: Age 21 and above			
Accommodation by September	0.0774 (0.1260)	0.0704 (0.0527)	0.1017* (0.0549)
Mean	0.05	0.34	0.39
# of observations	1,047	1,047	1,047

Notes: The table illustrates 2SLS estimates of different student outcomes on a dummy variable for having accommodation by September while instrumenting the treatment with lottery rank ($=1$ if ≤ 200). Panel A includes participants below age 21 and panel B includes participants aged 21 and above, where age is calculated as 2022 minus birth year. The estimates are calculated using the sample of lottery participants for whom there has been a detailed grade registered in the first academic year. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Balancing tests on heterogeneity samples

	N	Female	Age
Age <21	554	-0.0173 (0.0239)	
Age $\geq$21	1,047	-0.0070 (0.0161)	
Women	805		0.0030 (0.0030)
Men	796		-0.0022 (0.0027)

Notes: The table reports OLS estimates of lottery rank on pre-determined characteristics across different heterogeneity groups. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Balancing tests on survey samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Age	Female	Foreign background	Graduate	Study grant, t-1	Employment, t-1	Annual income, t-1
Dependent variable							
Panel A: All respondents							
Lottery rank (=1 if ≤ 200)	-0.2933 (0.4990)	-0.0085 (0.0699)	0.0064 (0.0691)	- -	- -	- -	- -
Mean	22.614	0.534	0.573	-	-	-	-
# of observations	560	560	560	-	-	-	-
Panel B: Restricted sample respondents							
Lottery rank (=1 if ≤ 200)	-0.3717 (0.2493)	0.0021 (0.1076)	-0.0090 (0.0436)	-0.0323*** (0.0120)	0.0914 (0.0820)	-0.0252 (0.1076)	-81.5461 (232.7704)
Mean	20.668	0.456	0.050	0.029	0.751	0.564	1055.925
# of observations	241	241	241	241	241	241	241
Panel C: Swedish respondents							
Lottery rank (=1 if ≤ 200)	-0.3417 (0.2521)	0.0268 (0.1103)	- -	-0.0340*** (0.0127)	0.0931 (0.0852)	-0.0222 (0.1094)	-67.6612 (238.7575)
Mean	20.699	0.454	-	0.031	0.742	0.585	1086.083
# of observations	229	229	-	229	229	229	229
Panel D: Newcomer respondents							
Lottery rank (=1 if ≤ 200)	-0.2147 (0.7423)	0.0002 (0.0920)	0.0144** (0.0072)	- -	- -	- -	- -
Mean	24.161	0.594	0.987	-	-	-	-
# of observations	310	310	310	-	-	-	-

Notes: The table reports OLS estimates of lottery rank on pre-determined characteristics. Panel A shows results for the full sample of survey respondents, Panel B for the restricted sample, Panel C for the Swedish sample, and Panel D for the newcomer sample. Immigrant, graduate, study grant, employment, and income are unavailable (marked -) for the All and Newcomer panels, since these characteristics rely on demographic and register data only available for participants in the Restricted and Swedish samples. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Multiple hypothesis testing

Outcome	Raw p-value	Adjusted p-value
Full-time employment	.000237898	.000713693
Part-time employment	.901001	.901001
Living in Lund	2.79531e-06	.0000125789
Having roommate	.0366625	.0824905
Social activities	.140864	.222537
Standardized grades	.173084	.222537
Top 10	.167202	.222537
Top 5	.455994	.512993
Housing Stability Index	1.01092e-07	9.09829e-07

Notes: The table reports the raw and adjusted p-values using Benjamini-Hochberg multiple hypothesis testing method. The raw p-values are obtained from the 2SLS regressions of several variables on an indicator of having accommodation by September, done on the full sample of Survey II respondents, using lottery rank lower than 200 as the instrument.

Table A11: Sensitivity to the choice of instrument threshold

		Average standardized grades				Top 5				Top 10			
		q<190	q<200	q<213	q<220	q<190	q<200	q<213	q<220	q<190	q<200	q<213	q<220
Panel A: All													
	Accommodation by September	0.1989**	0.2259**	0.1871*	0.1588*	0.0784*	0.0906**	0.0792**	0.0637*	0.1232***	0.1312***	0.1128***	0.0943**
		(0.1000)	(0.0994)	(0.0959)	(0.0934)	(0.0414)	(0.0403)	(0.0387)	(0.0371)	(0.0436)	(0.0425)	(0.0409)	(0.0394)
	# of observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601
Panel B: Swedish													
	Accommodation by September	0.2615*	0.3821**	0.3358*	0.3056*	0.0831	0.1216*	0.1168	0.0994	0.1277*	0.1695**	0.1598**	0.1414*
		(0.1563)	(0.1763)	(0.1834)	(0.1717)	(0.0662)	(0.0720)	(0.0725)	(0.0683)	(0.0703)	(0.0775)	(0.0780)	(0.0732)
	# of observations	608	608	608	608	608	608	608	608	608	608	608	608
Panel C: Newcomers													
	Accommodation by September	0.1866	0.1710	0.1523	0.1191	0.0797	0.0790	0.0664	0.0487	0.1369**	0.1266**	0.1070**	0.0845*
		(0.1293)	(0.1205)	(0.1135)	(0.1128)	(0.0525)	(0.0482)	(0.0460)	(0.0446)	(0.0554)	(0.0508)	(0.0487)	(0.0474)
	# of observations	891	891	891	891	891	891	891	891	891	891	891	891

Notes: The table reports 2SLS estimates of accommodation by September on standardized grades, top 5, and top 10, using instrumental variables with various rank thresholds. Robust standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

Table A12: First stage, reduced form, and IV using the continuous lottery rank

	Acc. by Sept.	Average standardized grades		Top 5		Top 10	
	First stage	RF	IV	RF	IV	RF	IV
Lottery rank (continuous, q)	-0.000177*** (0.000012)	0.000003 (0.000023)		0.000001 (0.000010)		-0.000003 (0.000010)	
Accommodation by September			-0.0191 (0.1323)		-0.0081 (0.0547)		0.0154 (0.0567)
Mean	0.087	0.04	0.04	0.33	0.33	0.38	0.38
# of observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601

Notes: The table reports first-stage, reduced-form, and 2SLS estimates using the continuous lottery rank q as the instrument, in place of the binary indicator (q<200) used in the main specification, on the full sample. Robust standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

Table A13: First-stage coefficients by lottery rank bin (All sample)

Rank bin	Coefficient	SE
100-200	-0.2558	(0.0811)
200-300	-0.6979	(0.0594)
300-500	-0.7624	(0.0550)
500-750	-0.7869	(0.0537)
750-1000	-0.7931	(0.0533)

Notes: First-stage coefficients of accommodation by September regressed on rank bin dummies (base category rank 0-100) for the full sample.

Table A14: Rank-bin instrument robustness check

	Average standardized grades	Top 5	Top 10
Panel A: All			
Accommodation by September	0.1313 (0.0835)	0.0512 (0.0336)	0.0754** (0.0355)
Mean	0.04	0.33	0.38
# of observations	1,601	1,601	1,601
First-stage F (rank bins)	69.79 (p= 0.000)		
Hansen J statistic	10.870	15.236	15.674
Hansen J p-value	0.144	0.033	0.028
Panel B: Swedish			
Accommodation by September	0.3126** (0.1543)	0.1198* (0.0631)	0.1401** (0.0654)
Mean	0.05	0.29	0.35
# of observations	608	608	608
First-stage F (rank bins)	15.62 (p= 0.000)		
Hansen J statistic	9.244	5.509	6.390
Hansen J p-value	0.236	0.598	0.495
Panel C: Newcomers			
Accommodation by September	0.0596 (0.0985)	0.0136 (0.0394)	0.0505 (0.0421)
Mean	0.02	0.36	0.39
# of observations	891	891	891
First-stage F (rank bins)	79.99 (p= 0.000)		
Hansen J statistic	15.222	18.078	20.575
Hansen J p-value	0.033	0.012	0.004

Notes: The table reports over-identified 2SLS estimates using a set of lottery rank bin dummies as excluded instruments for accommodation by September. Bins are defined at 0, 100, 200, 300, 500, 750, 1000, 1500, 2000, and 3000. Robust standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

Table A15: Bandwidth robustness of the main effect

		Average standardized grades				Top 5				Top 10			
		Full	q $\leq$ 1500	q $\leq$ 1000	q $\leq$ 700	Full	q $\leq$ 1500	q $\leq$ 1000	q $\leq$ 700	Full	q $\leq$ 1500	q $\leq$ 1000	q $\leq$ 700
Panel A: All													
Accommodation by September		0.2259**	0.2782**	0.2617**	0.3216**	0.0906**	0.1154***	0.0996**	0.0965*	0.1312***	0.1576***	0.1434***	0.1605***
		(0.0994)	(0.1083)	(0.1197)	(0.1414)	(0.0403)	(0.0439)	(0.0484)	(0.0561)	(0.0425)	(0.0463)	(0.0510)	(0.0596)
# of observations		1,601	937	642	450	1,601	937	642	450	1,601	937	642	450
Panel B: Swedish													
Accommodation by September		0.3821**	0.5047***	0.5413**	0.4540*	0.1216*	0.1568**	0.1554*	0.1028	0.1695**	0.2141**	0.2318**	0.1988*
		(0.1763)	(0.1934)	(0.2150)	(0.2434)	(0.0720)	(0.0777)	(0.0851)	(0.0942)	(0.0775)	(0.0839)	(0.0926)	(0.1026)
# of observations		608	370	252	170	608	370	252	170	608	370	252	170
Panel C: Newcomers													
Accommodation by September		0.1710	0.1862	0.1399	0.2385	0.0790	0.0924*	0.0679	0.0837	0.1266**	0.1393**	0.1085*	0.1413**
		(0.1205)	(0.1313)	(0.1439)	(0.1683)	(0.0482)	(0.0527)	(0.0578)	(0.0677)	(0.0508)	(0.0553)	(0.0605)	(0.0712)
# of observations		891	505	352	254	891	505	352	254	891	505	352	254

Notes: The table reports 2SLS estimates of the effect of accommodation by September (instrumented by lottery rank $q < 200$) on standardized grades, top 5, and top 10, across the full sample and three tighter restrictions to participants with lottery rank $q < 1500/1000/700$. Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A16: Descriptive statistics of Survey I respondents

	Survey I respondents	
	(1) Mean	(2) SD
Individual characteristics		
Age	21.45	3.13
Female	0.59	0.49
Accommodation preferences		
Preferred accommodation type:		
Corridor	0.26	0.44
Studio	0.48	0.50
Two bedroom	0.18	0.38
Three bedroom	0.08	0.28
Primary accommodation criterion:		
Distance	0.41	0.49
Rent	0.46	0.50
Size	0.09	0.28
State of the building	0.05	0.22
Educational characteristics		
Exchange student	0.03	0.18
Level of studies:		
Bachelor's level courses	0.80	0.40
Master's level courses	0.19	0.39
PhD program	0.02	0.13
Field of studies:		
Architecture	0.03	0.16
Arts and humanities	0.06	0.24
Business, administration and law	0.14	0.35
Engineering	0.25	0.43
Health and welfare	0.04	0.19
Information technologies	0.02	0.13
Natural science	0.16	0.37
Social science	0.30	0.46
# of observations	182	

Notes: The table presents descriptive statistics for Survey I respondents, showing the means and standard deviations for demographic characteristics, field of study, accommodation preferences, and level of study.

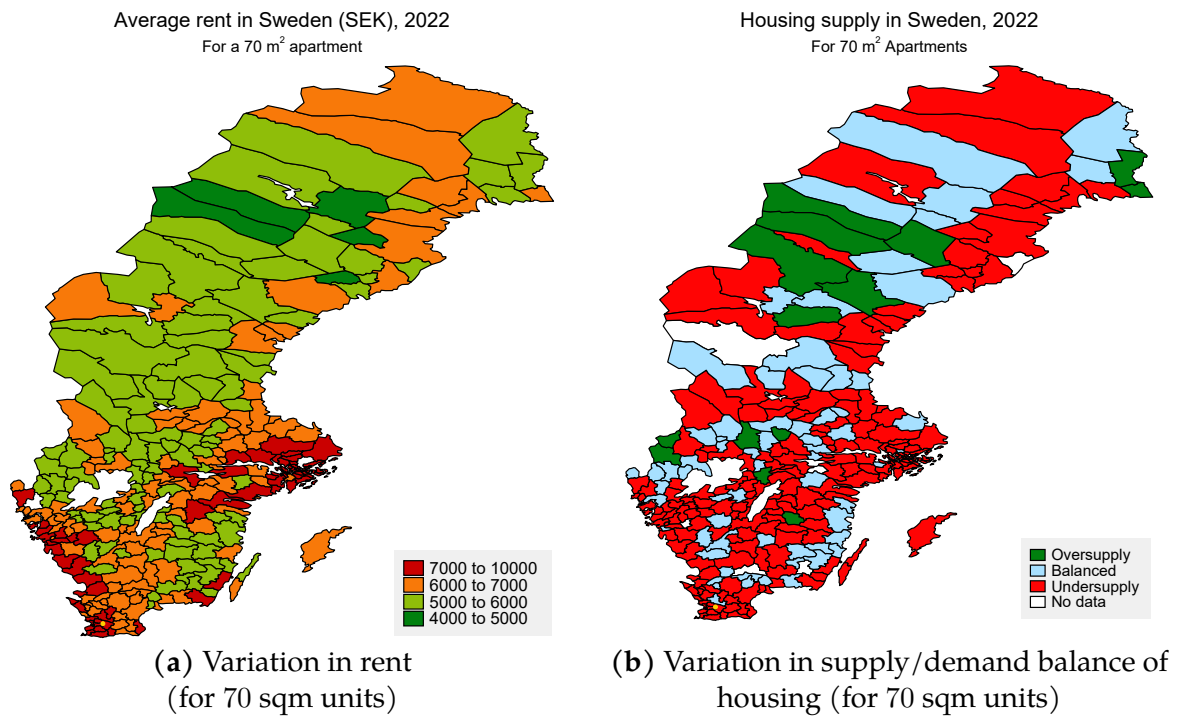
Table A17: Descriptive statistics of Survey II respondents

	Survey II respondents	
	Mean	SD
Individual characteristics		
Age	22.29	3.89
Female	0.57	0.49
Number of social activities (per week)	3.85	2.94
At least one parent with a university degree	0.77	0.42
Number of semesters of study:		
One semester	0.16	0.36
More than two semesters	0.71	0.46
Two semesters	0.13	0.34
Employment status:		
Unemployed	0.85	0.35
Full-time employment	0.02	0.13
Part-time employment	0.13	0.34
Current housing characteristics		
Having a roommate	0.66	0.47
Location of the residence:		
City of Lund	0.87	0.34
Lund municipality (not Lund city)	0.04	0.20
Skåne (not Lund municipality)	0.07	0.26
Other area	0.01	0.08
No answer	0.01	0.08
Contract duration		
Less than a month	0.03	0.16
Up to one semester	0.09	0.28
Up to one academic year	0.00	0.08
Entire study time	0.79	0.41
No answer	0.01	0.08
Notice period		
More than three months	0.01	0.12
Three months	0.14	0.35
Between one and three months	0.25	0.44
One month	0.47	0.50
Less than a month	0.02	0.13
No notice period	0.10	0.30
No answer	0.01	0.10
Type of contract:		
Own residence	0.02	0.14
Inherent	0.08	0.27
Tenancy, firsthand contract	0.70	0.46
Tenancy, secondhand contract	0.13	0.34
Other accommodation	0.06	0.25
No answer	0.01	0.09
# of observations	855	

Notes: The table presents descriptive statistics for Survey II respondents, showing the means and standard deviations of individual characteristics and current housing characteristics. The sample only includes the survey participants for whom there was gender and age variables available.

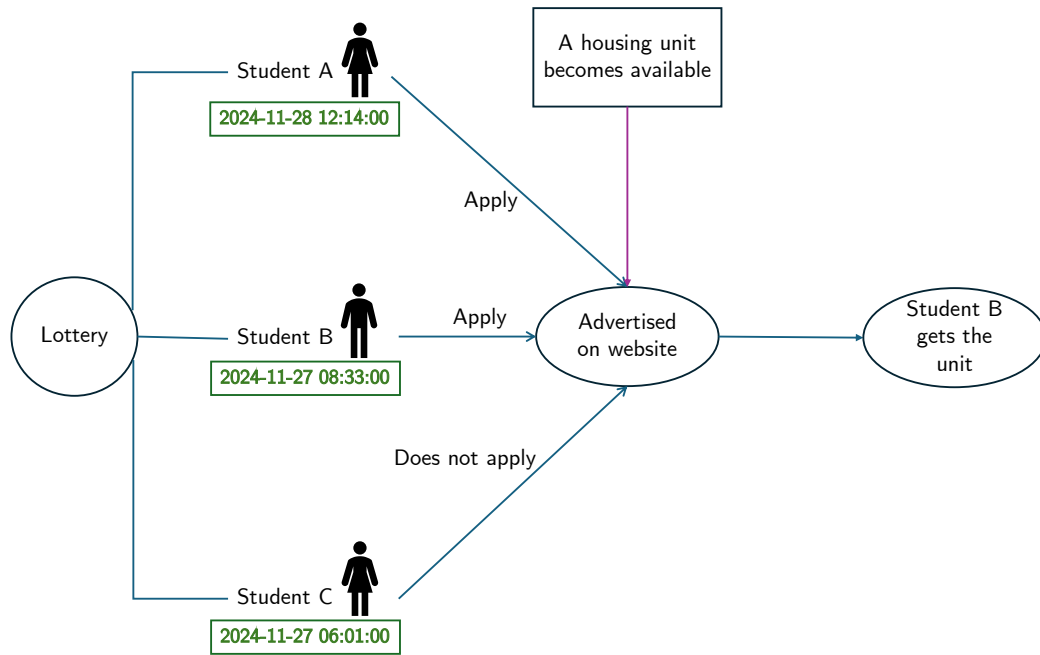
B Figures

Figure A1: Housing rent and supply variation across Sweden



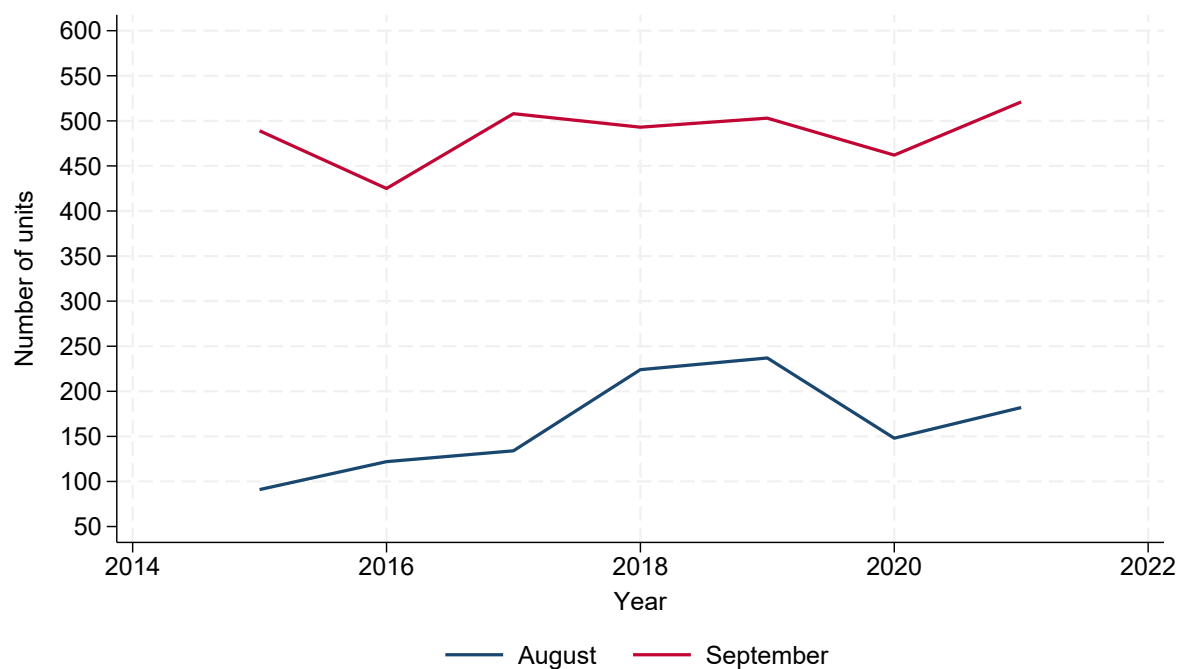
Notes: The figures above display the rent and housing supply variation across Sweden for 70 sqm units. The yellow dot marks the location of Lund Municipality. Data used to produce these figures was obtained from Bostadsmarknadsenkät 2022.

Figure A2: An illustrative example of AF's unit allocation



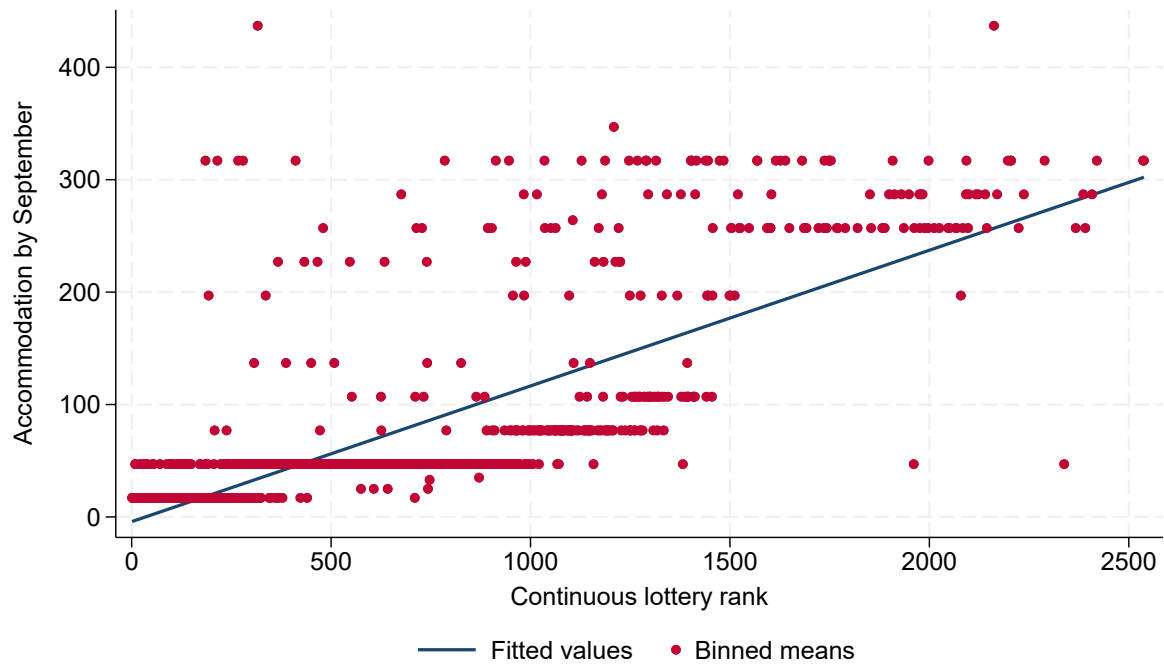
Notes: The illustration above shows a simplified, hypothetical example of how a unit is allocated once it becomes available. All three students received a lottery timestamp, but only Student A and Student B applied when the unit was advertised; Student C did not apply and is therefore not considered. Among the applicants, Student B's earlier timestamp (2024-11-27 08:33:00) gives her a better queue position than Student A's (2024-11-28 12:14:00), so Student B is offered the unit. Student A and Student C remain in the queue and can apply for another unit, when available.

Figure A3: Variation in the number of housing units available to lottery participants (2015-2021)



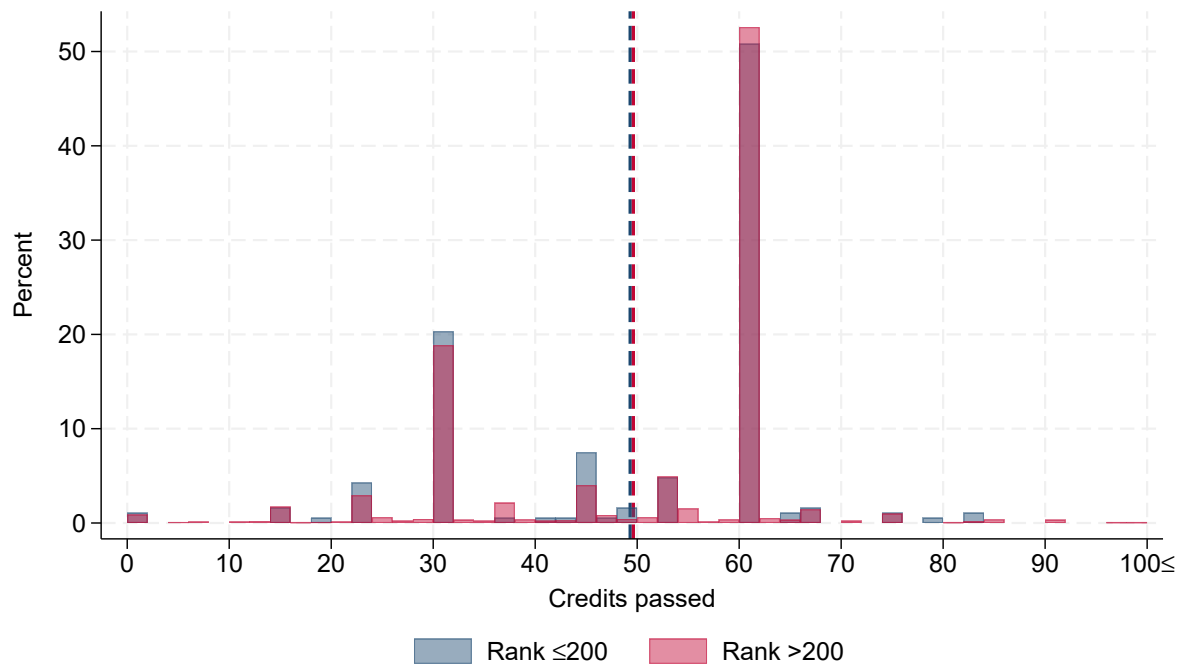
Notes: The figure above shows the variation in the number of housing units that became available to the lottery participants by AF in the months of August and September through years.

Figure A4: Relationship between lottery rank and time to secure student housing



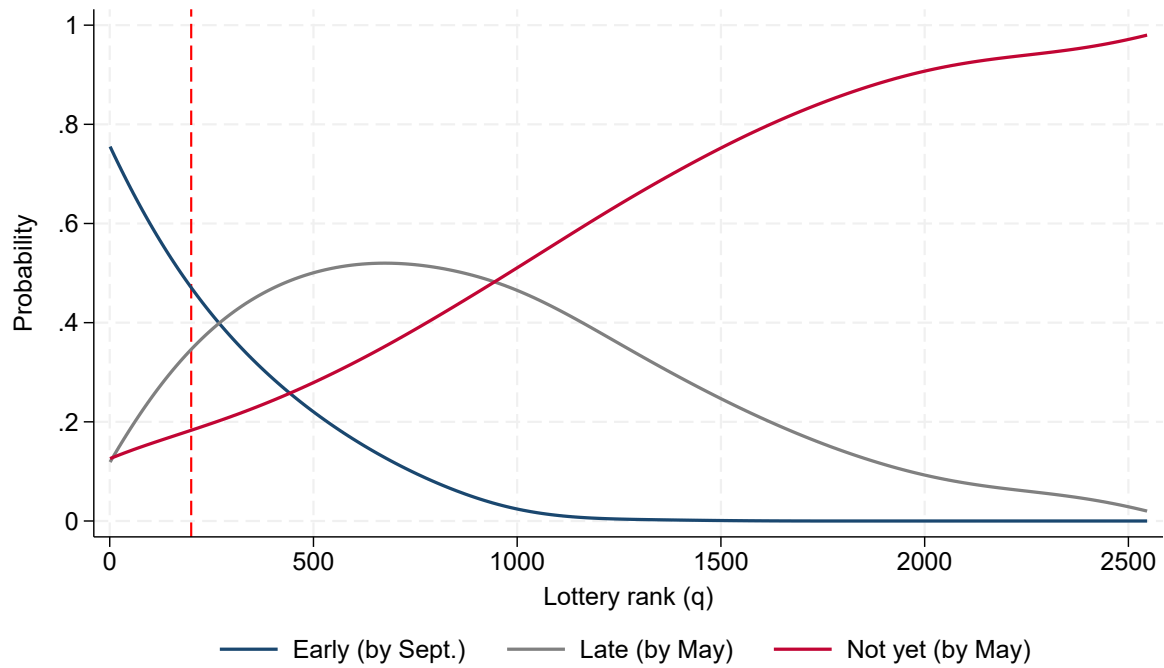
Notes: The figure above is a scatter plot depicting lottery ranks versus the number of days taken to secure accommodation for participants who obtained housing from AF within one year after the lottery. A fitted line is included to illustrate the relationship between lottery rank and the number of days it took to get student housing.

Figure A5: Number of credits registered for students by housing status



Notes: The figure above shows the distribution of credits passed by lottery participants in the first academic year, comparing those with a lottery rank below 200 to those with a rank above 200. The dashed lines show the average number of credits passed by each group.

Figure A6: Housing status by lottery rank



Notes: The figure shows lowess-smoothed probabilities, as a function of continuous lottery rank q , of belonging to each of three housing outcome groups in the first academic year: accommodated by the start of the academic year in September, accommodated later but within the observation window, or not yet accommodated by the end of the observation window. The dashed vertical line marks the $q < 200$ threshold used to construct the instrument.

Figure A7: Survey I

Lund University study on student accommodation access and educational outcomes - Preferences

Note: Participation in this study is voluntary and will not affect your position in the AF Bostäder housing queue, accommodation eligibility, and accommodation allocation.

Consent: By participation in this survey you consent to the processing of the personal data that you have provided for research purposes.

* Indicates required question

1. First name *

2. Surname *

3. Email *

4. Identification number

*

Please fill in your personal identification number (normal format: YYMMDD-NNNN). If you do not have a Swedish personal number you have been given an identification number by Lund university (Personal Code) or the Swedish tax authority

5. Level of studies in the ^{*}
upcoming semester

Mark only one oval.

- ☐ Bachelor's level courses
☐ Master's level courses
☐ PhD program

6. Exchange Student? ^{*}

Mark only one oval.

- ☐ Yes
☐ No

7. Field of studies ^{*}

8. What aspect do you care about the most ^{*}
in your accommodation?*

Mark only one oval.

- ☐ Distance to faculty
☐ Rent
☐ Size
☐ State of the building (newly built or renovated)

Rank your accommodation preferences from Most preferred ("1") to Least preferred ("4"):

9. Preference 1: *

Mark only one oval.

- ☐ Corridor room
- ☐ Studio / One-room apartment
- ☐ Two -room apartment
- ☐ Three-room apartment

10. Preference 2: *

Mark only one oval.

- ☐ Corridor room
- ☐ Studio / One-room apartment
- ☐ Two -room apartment
- ☐ Three-room apartment

11. Preference 3: *

Mark only one oval.

- ☐ Corridor room
- ☐ Studio / One-room apartment
- ☐ Two -room apartment
- ☐ Three-room apartment

12. Preference 4: *

Mark only one oval.

- ☐ Corridor room
- ☐ Studio / One-room apartment
- ☐ Two -room apartment
- ☐ Three-room apartment

Figure A8: Survey II

Lund University study on student accommodation access and educational outcomes - **January 2023 Round**

Note: Participation in this study is voluntary and will not affect your position in the AF Bostäder housing queue, accommodation eligibility, and accommodation allocation.

Consent: By participation in this survey you consent to the processing of the personal data that you have provided for research purposes.

.

* Indicates required question

1. Name *

2. Surname *

3. Identification number

*

Please fill in your personal identification number (normal format: YYMMDD-NNNN). If you do not have a Swedish personal number you have been given an identification number by Lund university (Personal Code) or the Swedish tax authority

4. Email *

5. 1. How long do you plan to study in Lund? *

Mark only one oval.

- ☐ One semester
☐ Two semester
☐ More than two semesters

6. 2. In addition to being enrolled in Lund University, do you work? *

Mark only one oval.

- ☐ Yes, full-time
☐ Yes, part-time
☐ No

7. 3. How many times in a week on average do you meet up with friends for socializing outside the university environment? *

Please only insert the number

8. 4. Do you have at least one parent with a university degree? *

Mark only one oval.

- ☐ Yes
☐ No

9. 5. Do you live at your current residence with one or more other people? *

Mark only one oval.

- ☐ Yes
☐ No

Notes: Survey I

10. 6. Are you living in AF accommodation already? (As of the end of **January 2023**) *

Mark only one oval.

- ☐ Yes
☐ No

If your answer to question 6 is "No", please answer questions 7 to 11:

If your answer is "Yes", you can skip the rest of the questions.

Questions 7 to 11:

Please answer the following questions according to your status in January 2023.

11. 7. Where do you live today?

Mark only one oval.

- ☐ City of Lund
☐ Lund municipality, not Lund city
☐ Skåne, not Lund municipality
☐ Other area

12. 8. How do you live today?

Mark only one oval.

- ☐ Hyresrätt, förstahandskontrakt / Tenancy, firsthand contract
☐ Hyresrätt eller bostadsrätt, andrahandskontrakt / Tenancy or co-operative apartment, second-hand contract
☐ Bostadsrätt, egen bostad / Co-operative apartment, own residence
☐ Inneboende / Inherent
☐ Annan boendeform / Other accommodation
☐ Vill ej uppge/ Do not want to mention

13. 9. How long can you stay at your current address?

Mark only one oval.

- ☐ The entire study time
- ☐ Up to one academic year
- ☐ Up to one Semester
- ☐ Less than a month

14. 10. How long do you want to stay at your current address?

Mark only one oval.

- ☐ Throughout the study period
- ☐ Until something better appears
- ☐ I want to move as soon as possible

15. 11. How long is the notice period today at your current address?

Mark only one oval.

- ☐ No notice period
- ☐ Less than a month
- ☐ One month
- ☐ Between one and three months
- ☐ Three months
- ☐ More than three months

C Compliers

Characterizing compliers using Abadie’s (2003) kappa-weighting. Let Z_i denote the instrument (lottery rank < 200) and D_i denote treatment (accommodation by September). I define the weight

$$\kappa_i = 1 - \frac{D_i(1 - Z_i)}{1 - P(Z = 1)} - \frac{(1 - D_i)Z_i}{P(Z = 1)}. \quad (3)$$

The instrument is unconditionally randomly assigned in my setting, since lottery rank is not stratified on observables. Because of this, $P(Z = 1)$ can be estimated simply as the sample share of students with $Z_i = 1$.

Abadie (2003) shows that for any covariate or outcome W , the complier-population mean can be recovered as

$$E[W \mid \text{complier}] = \frac{E[\kappa \cdot W]}{E[\kappa]}. \quad (4)$$

This expression reweights the observed sample so that always-takers and never-takers, defined here relative to accommodation by September, are effectively removed. It does this without requiring individual-level identification of complier status. I estimate $E[W \mid \text{complier}]$ as the sample analogue $\frac{\sum_i \kappa_i W_i}{\sum_i \kappa_i}$, and I construct standard errors using a nonparametric bootstrap with 500 replications, resampling students with replacement.

For comparison, I characterize the pooled population of non-compliers (always-takers and never-takers combined) in the same way, using the complementary weight $1 - \kappa_i$. My instrument is a single binary indicator with two-sided noncompliance, meaning both always-takers and never-takers, again relative to September accommodation, are present in the data. Because of this, the approach does not separately distinguish always-takers from never-takers. Doing so would require additional structure beyond simple kappa-weighting (e.g., Marbach and Hangartner, 2020).