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Dynamics of subletting: Evidence from Swedish university students☆

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ABSTRACT

Groups with more transient accommodation needs, such as students and expatriates, are increasingly turning to long-term rental sublets to satisfy their demand. We empirically analyze seasonality and market dynamics of such a market in the context of university admissions in Sweden. We find no difference in rents during the first half of the calendar year in student cities, followed by a sharp increase in August that stays persistent throughout the year. Student city listing density increases until May but is completely offset by September. During the subsequent 8 weeks following the university admission period, rents grow between 4.6 and 5.4 percent on average, while a one percentage point increase in the ratio of student net movement to population is associated with an increase in rent between 0.77 and 0.98 percent. Using a more robust subsample, we find that daily listing density in student cities decreases by 29.6 percent relative to non-student cities in the week immediately following the admission periods.

1. Introduction

Changes to life plans can arrive on short notice and can drastically impact an individual's demand for accommodation. Students, while waiting for admission results, face uncertainty about which city to call home in the near-future — at worst, this information is not revealed until only a few months or weeks prior to the start of the new academic year. Such quick shifts in the demand for housing can be hard to satisfy on the ownership market, both due to search frictions as well as budget and temporal constraints. The flexibility for landlords and tenants to bargain, and the associated high mobility and low risk relative to ownership, instead makes the rental market ideal to satisfy such accommodation needs. But even rental markets are faced with rigidities, often due to rent-setting regulations, long notice periods and inert allocation mechanisms. This is perhaps why groups with transient accommodation needs, whose demand can quickly shift, such as for students and expatriates, are turning to the market for sublets. In regions where sublet demand is reoccurring and pronounced enough, such as it can be in the lead-up to a new academic year (or job market cycle), seasonal fluctuations can materialize (Goodman, 1993; Saló et al., 2012; Ngai and Tenreyro, 2014).

The purpose of this study is to empirically investigate the seasonality and market dynamics of subletting, and we do this in the context of university admissions in Sweden. The market for long-term sublets continues to grow globally, and regulations on principal tenancies has made the long-term sublet market especially pronounced for Swedish students and expatriates.

We leverage a unique data set of sublet listings between January 31st, 2015 and January 18th, 2017 for the entirety of Sweden. Focusing on what we define as "student cities" – municipalities that host higher education institutions – we find no systematic difference in rents during the first half of the calendar year. Rents in student cities start increasing in July, and experience a drastic increase of 6.1 percent in August relative to January. This increase stays persistent for the remainder of the year. Listing density sharply increases until May but is completely offset by September. Non-student cities show consistent rent growth and little listing seasonality throughout the year. Contrary to recent evidence suggesting the existence of a "December discount" (Díaz and Jerez, 2013; Røed Larsen, 2024), we find no such evidence in our data.

To explain the uncovered seasonality, we hypothesize that the end of Summer marks a period of "return to school", which also drives sublet demand. In particular, we hypothesize that student demand mostly materializes on the subletting market. We show that student cities (compared to non-student cities) experience a statistically significant increase in rent in July – the same month as the first admission round – which is robust to lower-frequency time trends and the exclusion of larger municipalities. Rents in student cities (relative to non-student

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cities) increase by 4.6 percent during July to September. Listing density in student cities increases drastically until May but is completely offset by September, reaching negative levels throughout the rest of the year.

We probe this effect further by leveraging the granularity of our data. By utilizing both dichotomous and continuous treatment indicators, we assess average treatment effects and marginal changes in the net movement ratio of students to municipality population on rent levels.[1] We find statistically significant rent increases by around 5.4 percent in student cities after the last round of admissions, while a one percentage point increase in the net movement ratio is associated with a 0.77 percent increase in rent.

Due to the relative weight of larger student city municipalities, we assess a more robust subsample which covers approximately 40 percent of all net movers in the sample. We uncover effects of similar magnitude as when including larger municipalities, with rents rising by 5.2 percent relative to non-student cities in the post admission window. In terms of ratios, a one percentage point increase in the net movement ratio causes rents to rise by 0.98 percent and daily listing density to decrease by 5.9 percent over the restricted sample.

To assess the sensitivity of our main results and the results using the restricted sample, we conduct tests by creating treatment cities and placebo treatment timing, as well as assessing shared trends over *fake* outcomes using square meters, the number of rooms and average room size. We similarly test for randomized variation in treatment timing between student cities around the *de facto* treatment window.

Our study contributes to the literature on housing market seasonality by examining seasonal patterns on the market for long-term sublets. Previous research has established housing market mobility to be highly seasonal, with moves more likely to occur in the summer months accompanied by higher house prices and rents (Goodman, 1993; Saló et al., 2012; Ngai and Tenreyro, 2014). The determinants of seasonality are characterized by heterogeneity in the housing stock (Nenov et al., 2016), time-on-market and transaction volumes (Røed Larsen, 2024), and macroeconomic factors like unemployment and mortgage rates (Gan and Zhang, 2006; Hattapoglu and Hoxha, 2020). Pertaining to subletting markets, seasonality has predominantly been analyzed on markets for short-term sublets and tourism accommodation on platforms such as Airbnb (Juaneda et al., 2011; Martín et al., 2018; Benítez-Aurioles, 2021).[2] Long-term sublet accommodation generally lasts longer than a few days or weeks and is more of a 'semi-permanent' solution compared to platform rentals. Our study thus contributes by expanding the scope beyond the very short-term, by analyzing how reoccurring transient accommodation needs that arise due to sudden changes in life plans (i.e., university admissions) can shape subletting market seasonality.

Our study also contributes to a underdeveloped literature on student's housing demand and its subsequent impact on rent levels and housing availability. While evidence suggests that school calendars positively influence seasonality in the owner-occupied market (Goodman, 1993), the impact of higher education students' demand on rental markets is more ambiguous. At face value, the presence of a college or university causes housing services, as well as house prices and rents, to be higher (Ogur, 1973; Rivas et al., 2019). Mocanu and Tremacoldi-Rossi (2023) exploit the historical distribution of foreign enrollment in American college towns and find international student mobility to increase rents by approximately 1.3 percent and house prices by 2.5 percent between 2005 and 2015. Investigating 13 cities in the UK, Yilmaz et al. (2022) show that students' probability of renting is lower in the winter months, and the result is more pronounced when accounting for the distance from houses to university campuses. Baron and Kaplan (2011) look at the private rental market in Israel and find that increased student demand is negatively associated with rent. Our analysis contributes to this body of literature by widening the perspective, assessing student-associated seasonality and demand *in Sweden* on a rental market segment of *long-term sublets*.

The present paper is naturally linked, albeit still divergent, to the literature on the effects of rent control implementation (Skak and Bloze, 2013; Deschermeier et al., 2017; Diamond et al., 2019; Breidenbach et al., 2022; Mense et al., 2023). This is primarily because rent setting on Sweden's principal rental market is doubly-regulated and has been for more than half a decade: tenant associations have the power to decline rent increases and dwelling allocation happens through region-specific queues. These regulations have partly contributed to a need for flexibility through long-term subletting. Our results document high seasonality in this market, which particularly affects students. Principal tenants are protected from rent fluctuations due to the regulations — we provide auxiliary evidence that rent controlled apartments in Stockholm experience no statistically significant increase around the start of the academic year. This can potentially reinforce the *insider-outsider-dilemma* (Lindbeck, 2016; Riksbank, 2019), where *insider* principal tenants enjoy low-to-negative monetary costs of regulations, while *outsider* subletters have to pay high rents and deal with considerable rent fluctuations. In a sense, the Swedish rental market regulations achieve their goal of staving off (sudden) rent increases on the principal rental market. However, the average successful tenant on the principal rental market following university admissions is 37 years old in our sample, while the average age at graduation is 28 years old in Sweden. This suggests that, at least in Stockholm, it is not students who are the beneficiaries of the Swedish rent regulation. In fact, around 11 percent of renters in Sweden rent on the subletting market, which means that a minority of subtenants have to bear the costs to keep rent artificially low for a majority of principal tenants. The motivation for rent control and regulation is to stave of sudden and drastic rent increases and, by extension, be a tool for fairness by enabling access to the rental market across different socioeconomic statuses. Our results indicate that while such fairness-reasoning might *technically* be true for tenants on the principal rental market, i.e., the segment affected by rent regulation, it completely neglects groups active on the market for long-term sublets. Policy makers should be aware that rent regulation policies targeting a specific segment, no matter how fair and righteous they sound, can have adverse effects on other rental market segments and on the associated tenants.

The remainder of this paper is structured as follows: Section 2 presents the institutional setting and theory of sublet market seasonality. Section 3 presents the data material and summary statistics. Section 4 presents our empirical strategy and the results. Section 5 discusses our results and concludes.

2. Institutional setting

The Swedish subletting market. Virtually all principal tenancies in Sweden are distributed through a region-specific, centralized housing queue — be it a municipality or a county. Rent is negotiated between tenant and landlord associations and must by law follow rent levels of similar dwellings. Any rent increase must be accepted by the local tenant association, leading to asymmetric bargaining power in favor of tenant associations. This asymmetry, in conjuncture with dwelling allocation through the queue, has lead to a shortage of rental housing.

[1] We follow recent developments in the difference-in-differences literature, which includes, but is not limited to, Goodman-Bacon (2021), Borusyak et al. (2023), Roth (2022), Roth et al. (2023), Callaway et al. (2024).

[2] The literature on subletting markets has more generally examined how short-term subletting affects residential property values and rents (Horn and Merante, 2017; Chang, 2020; Duso et al., 2021; Reichle et al., 2023), segregation and discrimination (Ellen and Ross, 2018; Kakar et al., 2018; Marchenko, 2019), and crowding-out effects (Combs et al., 2020; Hill et al., 2023). Recent evidence documents the effects of global events such as the Covid-19 pandemic on rent levels, both for private rentals and tourism accommodation (Hesse and Vílchez, 2021; Tomal and Helbich, 2022).

This is most visible in the capital city of Stockholm, where time-in-queue for dwellings owned by the Stockholm Housing Agency exceeds 9 years in Stockholm county and 12 years in Stockholm municipality.[3]

The market for subletting has naturally developed out of necessity to aid those without enough time-in-queue to find appropriate housing. The right for Swedish tenants to sublet their dwelling for longer time periods was stipulated under the "Rental Law" act of 1968, although only under special circumstances.[4] The legislation came as a response to the increases in illegal subletting during the 1950's and 1960's, which itself was as a response to the need for increased mobility on the rental market — something that constrained principal tenancies could not provide (Christensen, 1994). A derivative of this system exists today, where sublets are distributed according to willingness-to-pay and rent is directly negotiated between tenant and subtenant.

Sublets are either owner-occupied dwellings or principal tenancies.[5] A private individual wishing to rent out their owner-occupied dwelling is formally subletting their apartment (as opposed to giving out principal tenancy) to a subtenant, as are principal tenants who wish to rent out their dwelling to a subtenant. Principal tenancy can only be awarded through the centralized queues. The Swedish National Board of Housing, Planning and Construction (2018) estimates that approximately 11 percent of renting households lived in a sublet in 2015, a number that most likely has increased since then.

Subletters of owner-occupied dwellings are allowed to cover operating costs and subletters of principal tenancies are allowed to add an additional 10 to 15 percent to the rent if the dwelling is rented out furnished. Recent studies show that rent often exceeds these specified thresholds, essentially enabling free price formation through subletters' willingness-to-pay.[6] As a result, rents for sublets are considerably higher than the rents for regulated principal tenancies. Fig. 1 shows average monthly rent between principal tenancies and sublets over this study's sample period (January 31st, 2015 – January 18th, 2017) in Stockholm county and Uppsala, over which principal tenancy rents grew by 5 percent and sublet rents by 32 percent. Table 1 shows some estimated differences in rent per square meter for principal tenancies and sublets. The data used in the present paper shows the per square meter sublet rents to be almost 100 percent higher than principal tenancy rents for the entirety of Sweden, and considerably higher in the Stockholm region.

Swedish higher education. The administration of Sweden is divided into counties, which themselves are divided into municipalities. As municipalities in the same county often share labor-, education-, and housing markets, there exists more informal definitions of "metropolitan areas" for larger municipalities and their periphery.[7] There are approximately 50 higher education institutions (public and private) spread across 24 municipalities (of 290 total municipalities) in Sweden's 21 counties.[8] In the present study, we refer to these 24 municipalities as "student cities.

The Swedish academic year starts in the transitional week from August to September — in the present study on August 31, 2015 (week 36) and August 29, 2016 (week 35). There are two rounds of admission leading up to the new academic year. The first round of admission passes during the second week of July, on July 9, 2015 (week 28) and July 12, 2016 (week 28), and the second round of admission passes during the first week of August, on August 4th, 2015 (week 32) and August 3rd, 2016 (week 31). There is another set of admissions during the Spring semester, but the number of applying and admitted students is a relatively minor compared to the primary admission round. This admission round is typically utilized by vocational programs, independent courses and classes, as well as some specific degree programs.[9]

Fig. 2 shows county level statistics of the average number of students coming in, consisting of newly admitted students and students returning from last year, and the average number of students going out, consisting of the number of graduated students at the end of the previous year. The period covers the entirety of the academic years 2015 and 2016. The figure only includes students who applied to, or graduated from, a full-time study program worth between 180 to 300 ECTS credits (3 to 5 years of full-time study).

Unsurprisingly, it is the biggest counties in terms of population – the counties of Stockholm, Västra Götaland (which houses Göteborg,[10]) and Skåne (which houses Malmö) – that also have the highest numbers of students coming in and going out, from almost 15,000 up to 20,000 students. Fig. 3 puts these numbers in relation to county population and also displays the ratio of the number of yearly sublet listings to county population based on the data set in the present study. These relative data paint a slightly different picture, as the counties of Kronoberg and Dalarna display the highest net-movement to population slightly above 1 percent. As can be seen in the supplementary online appendix A, this net movement ratio to municipality population is even higher in the student city municipalities of these counties, reaching as high as 2.7 percent in the municipality of Växjö (Kronoberg county) with a population of only 88,600, and 2.6 percent in the municipality of Falun (Dalarna county) with a population of only 57,300.

The yearly listing ratios highlight the general size of the subletting market in the larger metropolitan areas. Stockholm, Göteborg and Malmö, as well as older and popular student cities such as Uppsala (Uppsala county) and Lund (Skåne county), command a larger supply for sublets and have higher market activity. In fact, the ratio of yearly sublet listings to municipality population is the highest in Solna (Stockholm county; 1.3 percent), followed by Stockholm (1.0 percent), Lund (0.9 percent) and Uppsala (0.9 percent).

[3] The yearly welfare costs of these regulations have been estimated to be between 10 billion sek (approximately 1 billion usd) (The Swedish National Board of Housing, Planning and Construction, 2013) and 20 billion sek (approximately 2 billion usd) (Kopsch, 2021). Other adverse effects of these regulations include a shortage of rental housing and housing misallocation (Kopsch, 2019), as well as segregation based on education level, age and background (Fridell and Brogren, 2007; Enström Öst et al., 2014; Donner and Kopsch, 2023; Bratu and Bolotnyy, 2023).

[4] There have been various amendments and revisions to this act since then.

[5] In practice, owner-occupied dwellings generally means "tenant-ownership" dwellings (Swedish *"bostadsrätt"*). A cooperative usually owns multiple dwellings and sells the right of use to a buyer. Tenant-ownership dwellings usually consists of apartments in apartment buildings, while pure owner-occupied dwellings tend to be villas and semi-detached dwellings. Similar systems with tenant-ownership dwellings are found in Finland, Norway, Denmark, Germany, Austria and the Netherlands, to name a few. To sublet a tenant-ownership dwelling, the "owner" must apply for permission from the owning cooperative. To sublet a principal tenancy, the tenant must apply for permission from the landlord. All subletting without explicit permission is prohibited.

[6] Both "operating costs" and "furnished" are vaguely defined, resulting in well-documented higher-than-allowed sublet rents. Swedish authorities have recently clamped down on and prosecuted actors for selling subletting leases, but little has been done with regards to staving off the systematically higher-than-allowed sublet rents. For empirical estimates of these difference, see Herold (2019) and Stockholm Chamber of Commerce (2022).

[7] For instance, the "Stockholm metropolitan area" tends to include at least all of Stockholm county, and usually also parts of Uppsala county.

[8] Some of these municipalities house secondary and tertiary campuses in other municipalities, which are generally much smaller and focused on a particular branch of science. In this study, we focus on the main campuses in these 24 municipalities.

[9] According to the Swedish Higher Education Authority, the number of admitted students were approximately 80 600 and 16 300 at the start of the academic year and during Spring admissions, respectively.

[10] Göteborg has the English translation "Gothenburg", but due to the lack of translations for other counties and municipalities in Sweden, we will use "Göteborg" throughout for consistency.

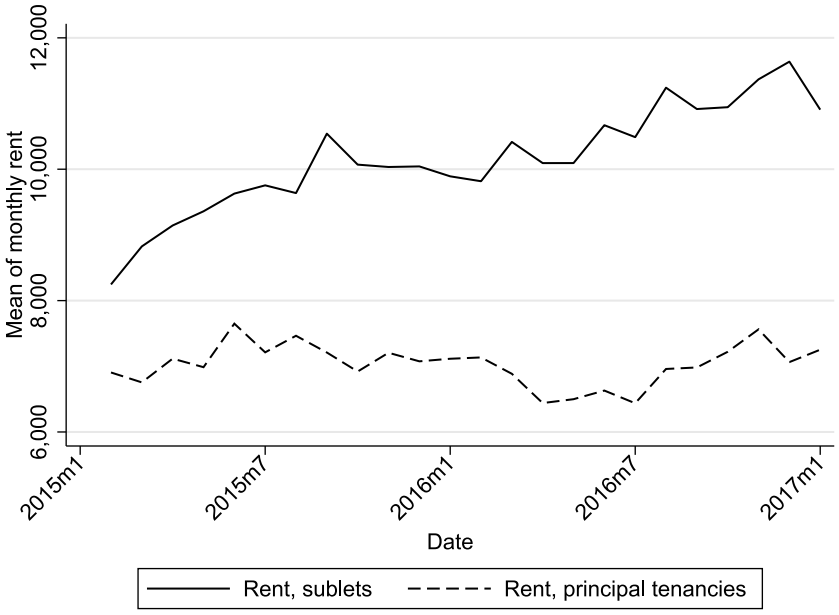

Fig. 1. Monthly rent for principal tenancies and sublets in Stockholm county and Uppsala municipality.

Table 1
Average rent per square meter for principal tenancies and sublets in Sweden.
Auxiliary Sources: Statistics Sweden.

Reference	Principal tenancies	Sublets	%-difference
Herold (2025) Period: *January 31, 2015 – January 18, 2017*			
Nation average	87 sek (8.26 usd)	172 sek (16.34 usd)	98%
Stockholm county	101 sek (9.59 usd)	235 sek (22.31 usd)	133%
Stockholm municipality	105 sek (9.97 usd)	260 sek (24.68 usd)	148%
Stockholm Chamber of Commerce (2022) Period: *January 2021 – December 2021*			
Nation average	100 sek (9.49 usd)	178 sek (16.90 usd)	78%
Stockholm county	111 sek (10.54 usd)	221 sek (20.98 usd)	99%
Stockholm municipality	118 sek (11.20 usd)	294 sek (11.20 usd)	149%
The Swedish National Board of Housing, Planning and Construction (2018) Period: *2009 – 2017*			
Nation average	82 sek (7.78 usd)	136 sek (12.91 usd)	66%
Stockholm county	94 sek (8.92 usd)	183 sek (17.37 usd)	95%

Note: The reported primary market rents comes from Statistics Sweden. The table aggregates rent levels for owner and rental sublets. The Swedish National Board of Housing, Planning and Construction (2018) does not provide an estimate for Stockholm municipality.

Subletting market seasonality and the academic year. In housing markets in general, buyers and sellers face search frictions which primarily materialize in the search for a match of good quality (Ngai and Tenreyro, 2014). This is predominantly an issue of information asymmetry, as sellers must screen potential buyers and buyers must locate and screen potential units. Search frictions should play a very limited role in the present context, simply because prospective subtenants are widely exposed to advertising of long-term sublets by newspapers, on social media and through word-of-mouth.

Given that the academic year is cyclical, students' demand for long-term sublets should presumably also be cyclical. Another, perhaps more salient, characterization for possible seasonality is thus given in terms of "hot" and "cold" seasons, or "thick" and "thin" markets. Search-and-match models exploring market thickness show that the probability of a good match is lower on "thin markets" with few buyers and sellers than on "thick markets" with more supply- and demand-side activity (Gan and Zhang, 2006; Gan and Li, 2016). Subletters are faced with the problem of subletting at a lower rent during the cold season or waiting until the hot season to sublet at a higher rent. Previous models show that the uncertainty of finding a better quality match in the hot season potentially induces the seller to accept this lower offer in the cold season.

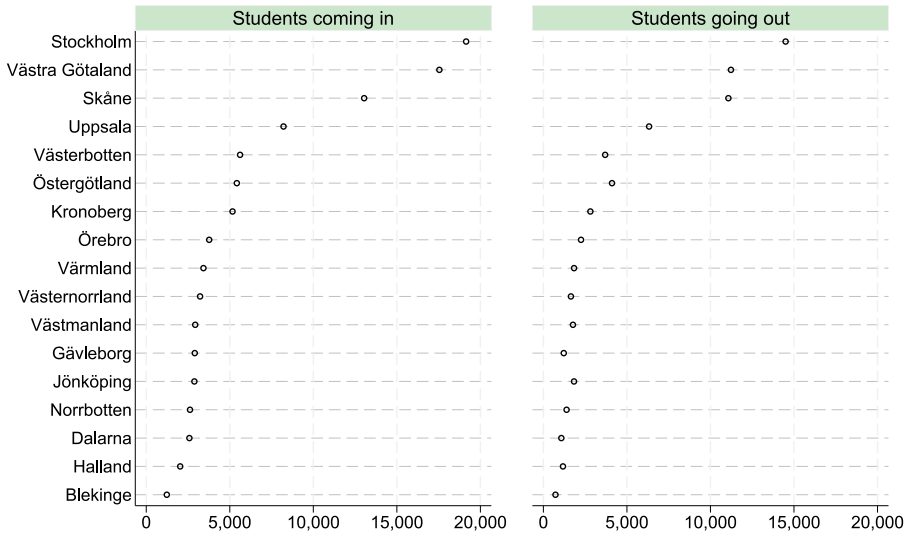

Fig. 2. Average annual students coming in and going out in 2015–2016.
Note: Students coming in are new admitted students and returning students from last year, and students going out is the number of graduated students at the end of the previous year for 2015–2016. See supplementary online appendix A for more detailed information at the municipality level. Source: Swedish Higher Education Authority.

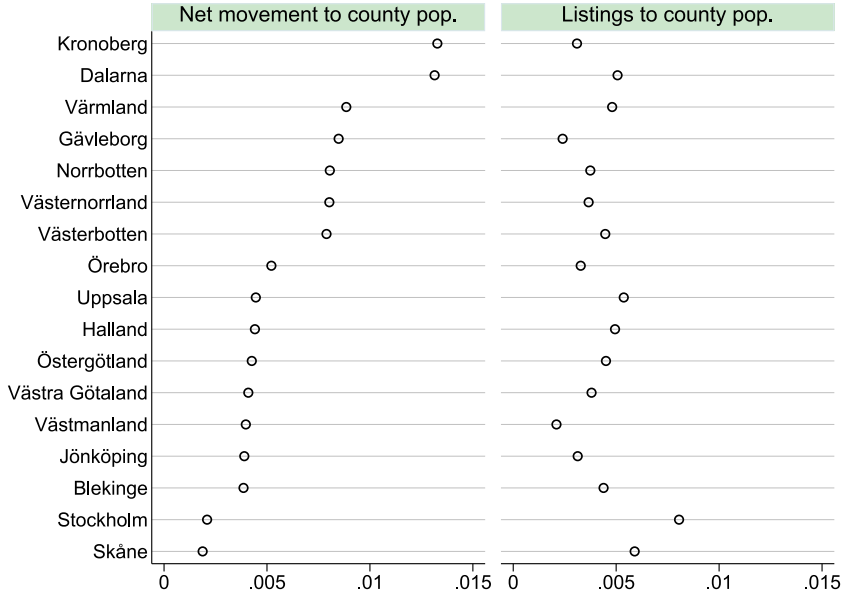

Fig. 3. Annual student turnover and listing density to county population, 2015–2016.
Note: Net-movement is defined as the difference in students coming in and student going out. Ratios are calculated towards the average annual county population for 2015–2016. Source: See supplementary online appendix A for more detailed information at the municipality level. Listings are from the data set of the present paper. Auxiliary sources: Statistics Sweden, Swedish Higher Education Authority.

The seasonality of the academic year means that subletters can anticipate increased demand following the admission period. Prospective subtenants, in turn, have very low probability of finding another match, let alone a better quality match, due to severe demand-side congestion, and are therefore forced to accept lower quality matches. This constraint binds harder the closer the search gets to the start of the academic year. Right by the terminal period, subletters should have near exclusive rights to dictate match quality by simply choosing their preferred subtenant, and have significant bargaining power relative to prospective subtenants.

To maximize their probability of finding a good match quality, forward-looking students commence their search for housing immediately after inferring admission acceptance. There is heterogeneity in this inferral — well performing students might infer close to their true probability of being accepted by comparing their academic performance to past admission requirements. It is therefore reasonable to expect some anticipation even prior to the first admission round, roughly two months before the start of the academic year. The severe demand-side congestion should conversely hinder some students from finding a match before the academic year starts, which spurs demand for a period after the start of the academic year. The increase in rent can therefore be persistent, which could further explain observed seasonality.[11]

[11] In theory, a share of students might strategically opt to wait out the initial demand and shift their own demand to later periods, if alternative, short-term living arrangements such as living on a friend's couch, commuting from a nearby city or by using platform rentals can be arranged. However, the persistence of the demand increase for sublets following the start of the academic year can be sticky and should largely offset such behavior.

Based on the above, we hypothesize that rent fluctuations on the long-term subletting market should be smaller in student cities compared to non-student cities before the "hot season", i.e., a yet undefined period around the start of the academic year. This is because most students are still waiting for their admission decision and subletters can wait until the hot season for a better match at a higher rent. The same dynamics should not be as pronounced in non-student cities. Subletters should slowly start increasing supply leading up to the academic year, initially to cater to first-round admitted students and subsequently as all applicants enter the market. Student city rents should start increasing relative to non-student cities and, following the terminal date, i.e., the second admission round, rents should see a sharp increase as all admission uncertainty is resolved. We further hypothesize that rents should remain at this higher level throughout the second half of the year compared to non-student cities, and subside when the "hot season" transitions back to the "cold season". Over time, as more matches are struck, supply should gradually decrease throughout the second half of the year.

3. Data and descriptive statistics

The present paper utilizes daily repeated cross-sectional list data for sublets from the Swedish website Blocket, with 232,728 observations running from January 31, 2015 to January 18, 2017. We drop listings with clearly incorrectly specified information, as well as listings that do not specify monthly rent, size in square meters and the total number of rooms available. We create listing characteristics dummies by quantifying free text that landlords have entered in the "description"-section of the listing, and code these variable with a 1 if the specified characteristic is present. In practice, any listing that in the description-section mentions the existence of a balcony gets coded with a 1, and all listings that do not specify this information get coded with a 0. This might lead to potential errors-in-variables, as listings that explicitly mention the absence of, e.g., a balcony, might accidentally be coded with a 1. As an intermediate step, we create indicator dummies that look for such negatives, i.e., the phrase "no balcony", which we then subtract from the main indicator, i.e., "balcony". This is done for every dwelling characteristic dummy. In total, we create 16 such listing characteristic dummy variables. As can be seen in the summary statistics presented in Table 2, only a small share of the listings report any of these characteristics. The type of dwelling is a factor variable ranging between 1 and 6 to indicate if the listing is a recreational home (=1), a yard (=2), an apartment (=3), a semi-detached house (=4), a room (=5) or a villa (=6). Listing characteristics also include square meters, number of rooms and average room size.

Observations are not uniquely identified in the sample, which presents challenges with the removal of duplicates. We identify and drop duplicate observations by matching on listing characteristics, municipality (on the district level for Stockholm, Göteborg and Malmö), and a year-quarter indicator. Specifying the year-quarter indicator allows for repeated observations over the year, but restricts the same listing from appearing more than once in a given quarter. In the case of duplicates in the same quarter, we choose to retain the most recent observation as it best reflects the dwelling's latest rent level. After this clean-up, the number of observations is reduced to 92,255 for the full sample. We provide kernel density plots over monthly rent, square meters and average room size, as well as their logarithms, in the supplementary online appendix C.

There are three shortcomings we wish to highlight. As with all list data, the listed rent might differ from the agreed-upon rent following a match. Previous research on the long-term subletting market in Sweden find little deviation between listed and actual rent: Stockholm Chamber of Commerce (2022) finds the actual rent to be 0.9 percent higher than the listed rent, indicating only a small upward-adjustment. Another caveat is that listings on Blocket might differ from other subletting listings on other rental websites, which could limit the generalizability of our results. Nonetheless, the sample used in the present study should be representative of the market for long-term sublets in Sweden, as Blocket is the most popular platform for sublets in Sweden and the most used portal for such transactions (The Swedish National Board of Housing, Planning and Construction, 2018). Lastly, certain dwelling characteristics can be excluded from the dummy variable indicators simply because the listing does not mention the existence of, e.g., a balcony, in the description-section. There is most likely some influence on our estimates by the omission of some of these characteristics.

4. Empirical analysis

4.1. Differences between student and non-student cites

Student cities tend to be the largest municipality in their respective county, which means that student and non-student cities are most likely not comparable on observables. Table 3 shows slow moving demographic, housing market and economic characteristics between the two divisions, as well as these statistics when excluding the municipalities of Stockholm, Göteborg and Malmö.[12] Student cities tend to have younger populations, a higher rate of rental and tenant ownership dwellings, and a stronger economic profile.

The average non-student city has a population size of 22,300, compared to student cities with populations averaging around 160,000. When excluding the big three, the average population size in student cities still reaches almost 106,400 individuals. The share of the population aged 20 to 39 years is considerably different, which is most likely the effect of a relatively younger student population and the pull of younger people to urban areas in general. Conversely, non-student cities have a noticeably larger share of older populations. This difference in the age distribution can also be reported in the self-reported struggle with alcohol, which is almost three percentage points higher in student cities. Student cities have a much larger share of both tenant ownership dwellings and rental dwellings compared to non-student cities, while non-student cities have a considerable higher prevalence of home-ownership. Both gross municipal product per capita, as well as median net income after taxes and transfers, are higher in student cities.

Table 4 presents the difference in means for some key variables in counties with both student and non-student cities. The counties of Gotland, Kalmar, Jämtland and Södermanland are excluded due to their lack of student cities. The monthly rent across Sweden is higher in student cities by around 694 sek (62 usd), while mean square meters, number of rooms and room size tend to be smaller. The number of daily listings is also higher in student cities, by approximately 14 listings per day. The mean rent difference is especially pronounced in Stockholm and Västmanland county, the latter with its student city Västerås. Interestingly, non-student cities in both Uppsala and Skåne county have a higher mean monthly rent despite the popularity of Uppsala University and Lund University (as can be seen in appendix A, the universities in Uppsala and Lund are the third and fourth most popular destinations in terms of students coming in). The balance table also highlights the relative weight of Stockholm, Västra Götaland and Skåne county in the sample, as they account for approximately 67 percent of all observations.

4.2. Seasonality over calendar months

Descriptive evidence of seasonality. To uncover seasonality, a first measure of inspection is to plot the log of monthly rent and the number of daily listings in student and non-student cities over the sample period, which we do in Fig. 4. The overall trend for the log

[12] Henceforth, we referred to the unit of Stockholm, Göteborg and Malmö as "the big three".

Table 2
Summary statistics for full sample of long-term sublets between January 31, 2015 and January 18, 2017.

	Mean	Median	SD	Min	Max	N
Non-student cities						
Nominal monthly rent	7,855.03	6,500	5,068.48	250	100,000	37,276
Number of daily listings	1.91	1	1.28	1	10	37,276
Square meters	80.68	65	87.12	1	1,800	37,276
Number of rooms	2.67	2	1.54	1	11	37,276
Average room size	31.34	26	36.67	0.33	900	37,276
The type of the dwelling (apartment, semi-detached, etc.)	3.67	3	1.22	1	6	37,276
Listing has at least one balcony	0.01	0	0.12	0	1	37,276
Listing has parking	0	0	0.03	0	1	37,276
Listing is rented out furnished	0.05	0	0.21	0	1	37,276
Listing is considered recently constructed	0.02	0	0.15	0	1	37,276
Listing is considered recently renovated	0.03	0	0.17	0	1	37,276
Listing is considered modern	0.01	0	0.08	0	1	37,276
Listing is considered close to the train station	0	0	0.03	0	1	37,276
Listing is considered centrally located	0.07	0	0.25	0	1	37,276
Listing is considered near campus	0	0	0.04	0	1	37,276
Listing has an indefinite lease	0.01	0	0.10	0	1	37,276
Listing has a short-term lease	0.01	0	0.09	0	1	37,276
Listing is considered a temporary rental	0	0	0.06	0	1	37,276
Listing is rented out around a special event	0.01	0	0.08	0	1	37,276
Listing is aimed towards a student tenant	0.02	0	0.13	0	1	37,276
Listing is aimed towards a woman tenant	0.01	0	0.09	0	1	37,276
Listing is aimed towards a male tenant	0	0	0.04	0	1	37,276
Student cities						
Nominal monthly rent	8,548.79	7,200	5,159.64	100	50,000	54,979
Number of daily listings	16.05	9	15.38	1	73	54,979
Square meters	62.46	50	79.08	1	2,000	54,979
Number of rooms	2.10	2	1.20	1	11	54,979
Average room size	30.29	25	39.14	0.67	1,518	54,979
The type of the dwelling (apartment, semi-detached, etc.)	3.26	3	0.80	1	6	54,979
Listing has at least one balcony	0.02	0	0.15	0	1	54,979
Listing has parking	0	0	0.03	0	1	54,979
Listing is rented out furnished	0.07	0	0.26	0	1	54,979
Listing is considered recently constructed	0.02	0	0.14	0	1	54,979
Listing is considered recently renovated	0.03	0	0.16	0	1	54,979
Listing is considered modern	0.01	0	0.08	0	1	54,979
Listing is considered close to the train station	0	0	0.04	0	1	54,979
Listing is considered centrally located	0.05	0	0.21	0	1	54,979
Listing is considered near campus	0.01	0	0.08	0	1	54,979
Listing has an indefinite lease	0.01	0	0.12	0	1	54,979
Listing has a short-term lease	0.03	0	0.16	0	1	54,979
Listing is considered a temporary rental	0	0	0.07	0	1	54,979
Listing is rented out around a special event	0	0	0.04	0	1	54,979
Listing is aimed towards a student tenant	0.03	0	0.16	0	1	54,979
Listing is aimed towards a woman tenant	0.01	0	0.12	0	1	54,979
Listing is aimed towards a male tenant	0	0	0.03	0	1	54,979
Full sample						
Nominal monthly rent	8,268.47	7,000	5,134.27	100	100,000	92,255
Number of daily listings	10.33	3	13.78	1	73	92,255
Square meters	69.82	56	82.90	1	2,000	92,255
Number of rooms	2.33	2	1.37	1	11	92,255
Average room size	30.71	25	38.16	0.33	1,518	92,255
The type of the dwelling (apartment, semi-detached, etc.)	3.43	3	1.01	1	6	92,255
Listing has at least one balcony	0.02	0	0.14	0	1	92,255
Listing has parking	0	0	0.03	0	1	92,255
Listing is rented out furnished	0.06	0	0.24	0	1	92,255
Listing is considered recently constructed	0.02	0	0.15	0	1	92,255
Listing is considered recently renovated	0.03	0	0.16	0	1	92,255
Listing is considered modern	0.01	0	0.08	0	1	92,255
Listing is considered close to the train station	0	0	0.03	0	1	92,255
Listing is considered centrally located	0.05	0	0.23	0	1	92,255
Listing is considered near campus	0	0	0.07	0	1	92,255
Listing has an indefinite lease	0.01	0	0.11	0	1	92,255
Listing has a short-term lease	0.02	0	0.14	0	1	92,255
Listing is considered a temporary rental	0	0	0.06	0	1	92,255
Listing is rented out around a special event	0	0	0.06	0	1	92,255
Listing is aimed towards a student tenant	0.02	0	0.15	0	1	92,255
Listing is aimed towards a woman tenant	0.01	0	0.11	0	1	92,255
Listing is aimed towards a male tenant	0	0	0.03	0	1	92,255

Note: The sample consists of 21 counties and 287 municipalities (out of 290 total municipalities in Sweden). The type of the dwelling is a factor variable ranging between 1 and 6, with "apartment" equal to 3. See supplementary online appendix B for detailed summary statistics over counties between student and non-student cities.

Table 3
Slow-moving characteristics of student and non-student cities between 2014 and 2016.
Auxiliary Sources: Statistics Sweden, Swedish Association of Local Authorities and Regions.

	(1) Non-student cities	(2) Student cities	(3) Student cities
Big three excluded		No	Yes
Demographics			
Total population	22,272	160,114	106,369
Share of population aged 0 to 19 years	21.57	21.58	21.50
Share of population aged 20 to 39 years	21.43	28.75	27.58
Share of population aged 40 to 59 years	25.99	24.86	24.77
Share of population aged 60+	31.01	24.81	26.16
Share of unemployed the past year, ages 20 to 64	5.97	5.90	6.00
Share of self-reported struggles with alcohol, ages 16 to 84	13.79	16.45	15.71
Housing market characteristics			
Share of tenant ownership dwellings	11.72	25.48	21.57
Share of rental dwellings	29.92	40.82	40.67
Share of owner occupied dwellings	58.36	33.70	37.76
Economic characteristics			
Gross municipal product, 1,000 sek/capita	307.85	488.62	412.11
Median net income after taxes and transfers, ages 20 to 64	216,048	224,424	221,380

Note: The table reports the means for each group. For admission information for student cities, see supplementary online appendix A.

Table 4
Within-county difference in means ($\mu_k^{Non-student} - \mu_k^{Student}$) between student and non-student cities. Standard deviation in parenthesis.

	Monthly rent	Square meters	Number of rooms	Room size	Daily listings	N
Sweden	−693.75***	18.22***	0.57***	1.05***	−14.14***	92,255
	(34.25)	(0.56)	(0.01)	(0.25)	(0.07)	
Blekinge	−86.69	16.95***	0.48***	0.14	−0.43***	1,175
	(147.51)	(3.65)	(0.08)	(1.63)	(0.05)	
Dalarna	78.04	8.89	0.48***	−4.19	−0.55***	1,193
	(198.45)	(6.29)	(0.08)	(3.65)	(0.06)	
Gävleborg	109.26	19.48***	0.64***	−0.26	−0.69***	987
	(162.36)	(5.06)	(0.08)	(2.62)	(0.05)	
Halland	1739.27***	17.72***	0.69***	−0.98	−1.05***	1,983
	(166.11)	(2.91)	(0.07)	(1.15)	(0.06)	
J̀onḱoping	−190.04	24.77***	0.76***	3.28*	−1.35***	1,723
	(122.14)	(4.24)	(0.07)	(1.77)	(0.05)	
Kronoberg	−131.78	35.01***	0.92***	2.41	−0.75***	1,130
	(159.02)	(7.29)	(0.09)	(2.84)	(0.05)	
Norrbotten	−266.34	22.62***	0.42***	5.63**	−0.99***	1,174
	(214.87)	(5.77)	(0.09)	(2.65)	(0.05)	
Skåne	418.89***	23.62***	0.77***	0.48	−4.32***	12,714
	(68.34)	(1.49)	(0.03)	(0.63)	(0.05)	
Stockholm	−866.84***	15.06***	0.37***	1.71***	−26.20***	37,110
	(66.01)	(0.82)	(0.02)	(0.36)	(0.10)	
Uppsala	179.78	23.79***	0.85***	0.95	−6.44***	4,681
	(161.73)	(4.16)	(0.07)	(2.15)	(0.06)	
Värmland	−595.21***	16.19***	0.71***	−3.10	−1.23***	1,768
	(129.34)	(4.19)	(0.07)	(1.99)	(0.05)	
Västerbotten	−522.54***	−8.06*	0.50***	−11.09***	−3.13***	2,240
	(135.21)	(4.54)	(0.07)	(1.86)	(0.06)	
Västernorrland	−515.99***	10.93**	0.60***	−3.01	−1.23***	1,479
	(128.20)	(4.64)	(0.07)	(2.10)	(0.06)	
Västmanland	−855.42***	18.72***	0.58***	4.99**	−1.16***	1,261
	(182.41)	(5.17)	(0.09)	(2.51)	(0.06)	
V̀astra Ǵotaland	−531.94***	24.91***	0.77***	1.96***	−9.96***	12,049
	(79.91)	(1.69)	(0.03)	(0.75)	(0.07)	
Örebro	−383.32***	21.60***	0.76***	0.93	−2.24***	1,960
	(118.35)	(5.19)	(0.07)	(2.45)	(0.05)	
̀Osterǵotland	−328.41***	3.18	0.31***	−2.23	−1.56***	2,836
	(109.05)	(3.39)	(0.05)	(1.92)	(0.06)	

Note: Means are computed for $\mu_k^{Non-student} - \mu_k^{Student}$ for variable k. The sample consists of 21 counties and 287 municipalities (out of 290 total municipalities in Sweden). See supplementary online appendix B for detailed summary statistics.

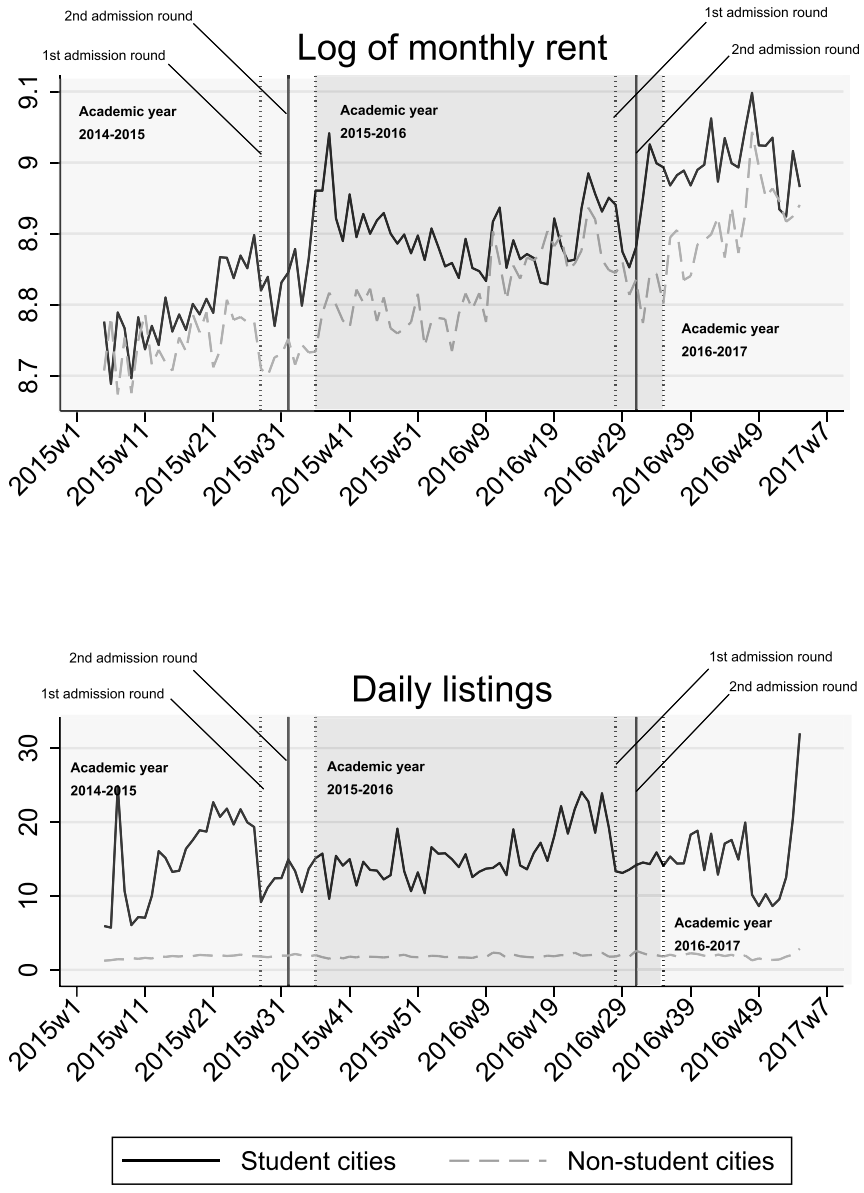

Fig. 4. The log of monthly rent and daily listing density over the sample period.
Note: The sample period stretches from January 31, 2015 in the middle of the academic year 2014-2015, and ends on January 18, 2017, in the middle of the academic year 2016-2017. The official start dates are August 31, 2015 (week 36) and August 29, 2016 (week 35), with the first admission round passing on the July 9, 2015 (week 28) and July 12, 2015 (week 28) and the second admission round passing on August 4, 2015 (week 32) and August 3, 2016 (week 31).

of monthly rent is similar between the two groups throughout the first half of 2015, but rises considerably in student cities leading up to both admission rounds. Following the start of the academic year, rent slowly reverts back to the level of non-student cities throughout the rest of the year, only for a similar pattern to emerge again in 2016. Average daily listing density is considerably higher in student cities compared to non-student cities, and while both show relatively stable development throughout the sample period, there is more week-to-week variation in student cities. In particular, the number of listings decreases sharply right before the first admission round passes in both 2015 and 2016.[13]

Next, we regress separate models for student and non-student cities to compare the monthly temporal fluctuations within groups. We assume that rent follows a hedonic pricing framework and sums up to the monetary value of the dwelling's relevant characteristics. We fit a model of the form

$$ln(rent_{i,m,t}) = \gamma\, month_t + FE_m + FE_t + x_i'\beta + u_{i,m,t} \quad (1)$$

where the dependent variable $ln(rent_{i,m,t})$ is the log of monthly rent for listing i in municipality m at day t. $month_t$ is a set of calendar dummies for the months of February through December, with γ being the coefficient. January enters as reference and the estimates are therefore put in relation to this month. x_i' is a 1×20 vector containing time-invariant listing characteristics and β is the vector of coefficients. FE_m are municipality-district specific fixed effects[14] and

[13] For similar development of square meters, room size and the number of rooms, see supplementary online appendix D. As can be seen in supplementary online appendix E, student city daily listing density is more seasonal compared to non-student cities, with higher local maxima and lower local minima over the sample period. Conversely, non-student daily listing density is relatively flat throughout most of the sample period.

[14] For the municipalities of Stockholm, Göteborg and Malmö, the fixed effects are at the district level.

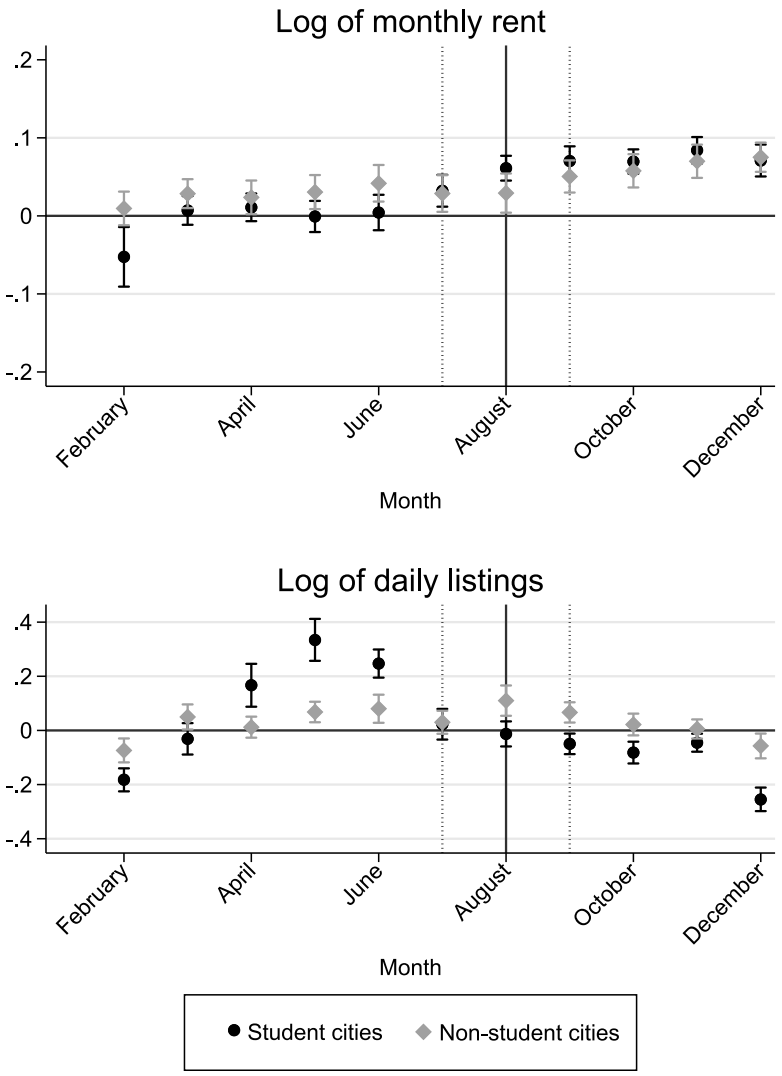

Fig. 5. Regressions of month dummies for separate subsamples of student cities and non-student cities, 2015–2016.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. Reported are the 95% confidence intervals. The first admission round passes on July 9, 2015 (week 28) and July 12, 2015 (week 28) (marked by the first dotted line), the last admission round passes on August 4, 2015 (week 32) and August 3, 2016 (week 31) (marked by the full line), and the academic year starts on August 31, 2015 (week 36) and August 29, 2016 (week 35) (marked by the second dotted line). January 2015 and 2016 enter as reference.

FE_t are year-specific fixed effects. $u_{i,m,t}$ is a normally distributed, zero mean and constant variance, error term. We cluster standard errors at the municipality-district level throughout the analysis.

We accompany the above specification with a similar model using listings at the municipality-day level of the form

$$ln(listings_{m,t}) = \gamma\, month_t + FE_m + FE_t + x'_{m,t}\beta + u_{m,t} \quad (2)$$

where the dependent variable $ln(listings_{m,t})$ is the log of the number of listings in municipality m during day t. We use the log of daily listings (as opposed to its raw count) for normalization and to allow for relative interpretation.[15] $x'_{m,t}$ is now the average listings characteristics in a particular day t in municipality m.

The regression output is presented in Fig. 5, with the upper panel displaying the log of monthly rent and the lower panel displaying the log of daily listing density. There is clear and pronounced seasonality in both student and non-student cities. Student cities show no effect statistically different from zero between March and June, compared to January. Rents start increasing in July and experience a sharp jump of 6.1 percent in August. Rents stay at this elevated level for the remainder of the year. On the other hand, there is statistically significant effect in rent in non-student cities already in March, which persistently increases throughout the year. A somewhat similar spike to the one in August in student cities occurs in non-student cities in September, albeit of smaller magnitude.

The log of daily listing density is clearly on separate trends in student cities and peaks in May at approximately 33 percent higher relative to January. The decline starts in June and reaches statistically insignificant levels in July. By September, daily listing density is statistically lower compared to January. The pattern for daily listing density in non-student cities appears similar relative to January, with statistically higher levels in May, June, August and September. Interestingly, the "December"-discount uncovered in the literature (Díaz and Jerez, 2013; Røed Larsen, 2024) shows no material manifestation in rents across both groups. In fact, while lower listing density could indicate

[15] Running the same model using the raw count of daily listing density yields the same overall result, but due to the higher listing density in student cities, it obscures the effect in non-student cities.

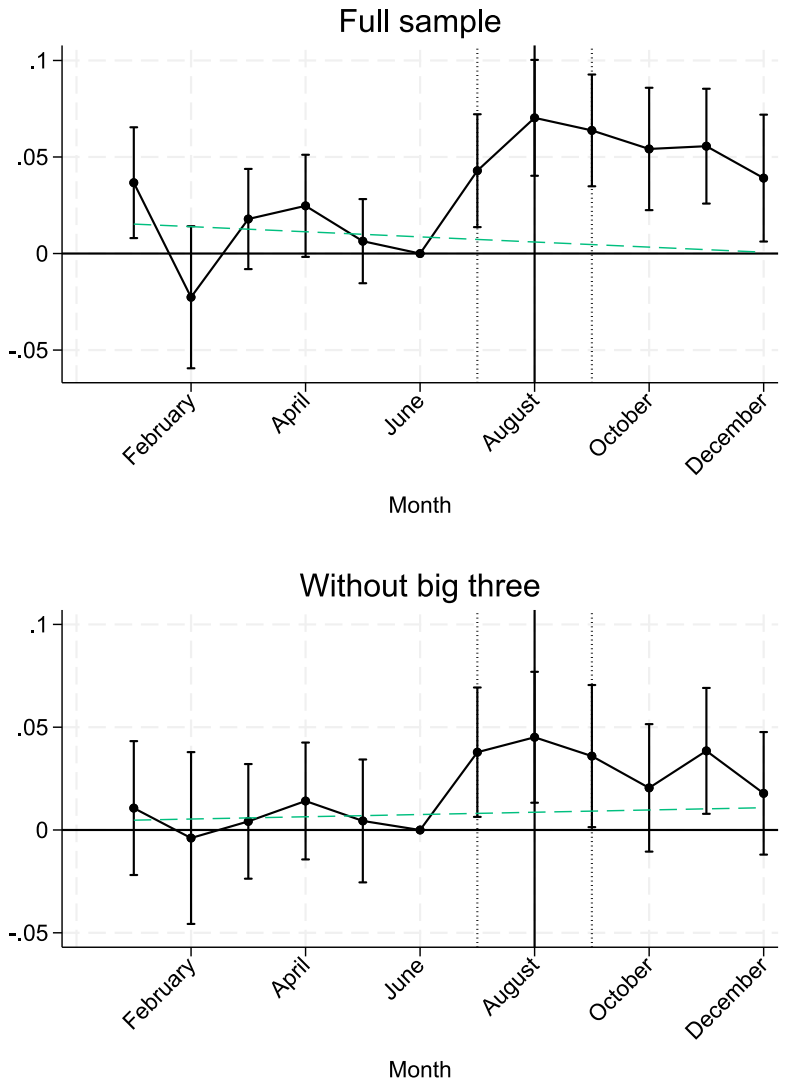

Fig. 6. Log of monthly rent in full sample and without the big three over the sample period, 2015–2016.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. Reported are the 95% confidence intervals. The first admission round passes on July 9, 2015 (week 28) and July 12, 2015 (week 28) (marked by the first dotted line), the last admission round passes on August 4, 2015 (week 32) and August 3, 2016 (week 31) (marked by the full line), and the academic year starts on August 31, 2015 (week 36) and August 29, 2016 (week 35) (marked by the second dotted line). June 2015 and 2016 enter as reference.

lower match quality compared to other months throughout the year, it is not visible in rent levels .

Fig. 5 lends credence to our previous hypothesis that the number of listings in student cities start increasing as the distance to the start of the academic year diminishes. Without claims of causality, a potential explanation is that subletters anticipate the start of the academic year and are making their units available for rent during the first half of the year. The sharp increase in daily listing density is not reciprocated with any statistically meaningful effect on rents, perhaps as students are still waiting for an admission response. In June, there is then a small decline in listings due to increased matching as prospective students are entering the market. In July, we see a statistically significant increase in monthly rent and drastic decrease in listings, possibly due to the influx of prospective subtenants following the first round of admission. By August, both admission rounds have passed and all relevant market participants enter, which could explain the spike in student city rent. The rent level then remains at this higher level while listings steadily decrease throughout the second half of the year, possibly as excess demand diminishes.

Difference-in-differences over calendar months. We hypothesize that part of the observed seasonality in the market for long-term sublets can be attributed to the start of the academic year, particularly in student cities. By using a difference-in-difference design, we assess the effect of the admission window starting in July, using June as the reference period. This approach allows us to assess whether the trends between student and non-student cities differed before the admission rounds and allows us to isolate the impact of the admission rounds relative to this baseline period. We fit two models of the form

$$ln(rent_{i,m,t}) = \gamma\, month_t + \phi\, studentcities_m + \delta\, month_t \times studentcities_m + FE_m + FE_t + x_i'\beta + u_{i,m,t} \quad (3)$$

and

$$ln(listings_{m,t}) = \gamma\, month_t + \phi\, studentcities_m + \delta\, month_t \times studentcities_m + FE_m + FE_t + x_{m,t}'\beta + u_{m,t} \quad (4)$$

where now, $studentcities_m$ enters as indicator taking the value 1 if the observation is in a student city, and the $month_t \times studentcities_m$ is its interaction on the same $month_t$ indicator from Eqs. (1) and (2). δ is the coefficient of interest and captures the effect of this interaction.

The estimation is plotted for the log of monthly rent in Fig. 6 and the log of daily listings in Fig. 7. There is a statistically different effect

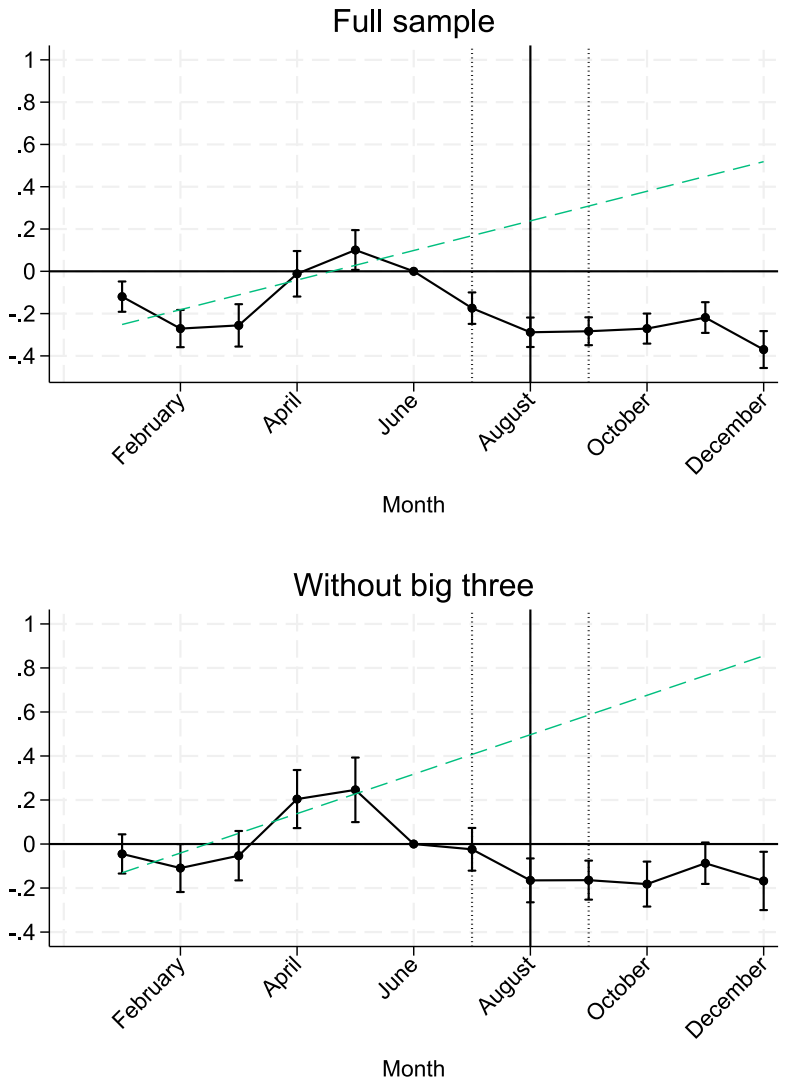

Fig. 7. Log of daily listings in full sample and without the big three over the sample period, 2015–2016.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. Reported are the 95% confidence intervals. The first admission round passes on July 9, 2015 (week 28) and July 12, 2015 (week 28) (marked by the first dotted line), the last admission round passes on August 4, 2015 (week 32) and August 3, 2016 (week 31) (marked by the full line), and the academic year starts on August 31, 2015 (week 36) and August 29, 2016 (week 35) (marked by the second dotted line). June 2015 and 2016 enter as reference.

on rents in January during the pre-event period, and almost an overcorrection in February, which somewhat stabilizes for the remainder of the pre-admission window period. When we restrict the sample to exclude the big three, the significance of this period goes away and the overall trend is much more stable. The observed positive effect in July remains for both specifications. In July, the log of monthly rent increases by 4.3 percent in the full specification and by 3.8 percent when excluding the big three. This effect peaks in August, reaching 7.0 percent in the full specification and 4.5 percent when excluding the big three, and then diminishes over time.

A similar pattern as in Fig. 5 emerges for the daily listing density. The pre-admission period from January to March is statistically different from zero and negative, with a steep upwards correction in April and May. When we restrict the sample to exclude the big three, the statistical significance in the months of the first quarter goes away but anticipatory effects in April and May instead gain significance. The pre-admission trend is sharply increasing, which is noticeably divergent from the uncovered effects in the post-admission period. As shown in supplementary online appendix F.2, the overall volume of daily listings is higher in the counties containing larger municipalities such as Stockholm, Göteborg, Malmö and Uppsala — all of which are student cities. These counties show a clear upwards trend in the period leading up to the second admission window, which likely can explain a large part of the divergence in pre-admission trends in Fig. 7.

We continue by pooling the period post-June to capture the period between July and September and the period from October to December separately. The advantage in doing so is that we can infer about average effects in the post-admission period compared to all months in pre-admission period. Due to the noise in daily listing density, we solely focus on the log of monthly rent. The results are presented in Table 5. With this specification, the immediate post-June period shows an increase in rent of around 4.6 percent in the full sample and 3.3 percent when excluding the big three. In both samples, the latter period from October to December is smaller, albeit still significant. The result are robust to lower-frequency time trends.

4.3. Seasonality over event weeks

Event week estimation. The difference-in-difference estimation over calendar months seem to indicate positive treatment effects on

Table 5
Regression output over calendar months.

	(1) Full sample	(2)	(3)	(4) No big three	(5)	(6)
Dependent variable	Baseline	Quarterly	Yearly	Baseline	Quarterly	Yearly
Log of monthly rent	model	trend	trend	model	trend	trend
Interaction with period July–September	0.0463***	0.0458***	0.0463***	0.0331***	0.0353***	0.0311**
	(0.0108)	(0.0108)	(0.0109)	(0.0123)	(0.0126)	(0.0124)
Interaction with period October–December	0.0390***	0.0375***	0.0396***	0.0207**	0.0249**	0.0186*
	(0.00971)	(0.0103)	(0.00996)	(0.00932)	(0.00998)	(0.00976)
Observations	92,255	92,255	92,255	60,752	60,752	60,752
R-squared	0.610	0.612	0.612	0.612	0.614	0.614
Listing characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors clustered on the municipality-district level in parenthesis. See supplementary online appendix I.1 for estimated effects of covariates.

rent in student cities, but the low granularity omits important higher-frequency temporality. In particular, the last admission round and parts of the start week of the academic year (2015, week 36; 2016, week 37) are pooled into the month of August, which makes it difficult to distinguish the effects of the admission rounds from the academic start date — is it the passing of the second admission round or the start of the academic year (or both) that drives the peak in August? By aligning observations relative to the timing of these events, expressed in event weeks, we can more precisely estimate the causal effects of the admission rounds from the start date of the academic year and capture more granular late-summer seasonality.

We restrict the sample to focus only on the first half of the year, starting from February 1st and running until September 30th in both 2015 and 2016. We start by breaking down the time period into separate weeks in order to assess the validity of the common-trends assumption. This specification takes the form

$$\begin{aligned} ln(rent_{i,m,t}) = & \sum_{j=\{-24,-8\}}^{8} \gamma^j event\_week_t^j + \phi\, studentcities_m \\ & + \sum_{j=\{-24,-8\}}^{8} \delta^j (studentcities_m \times event\_week_t^j) \\ & + I_t + FE_m + FE_t + \mathbf{x}_i'\beta + u_{i,m,t} \end{aligned} \tag{5}$$

where j indicates the week relative to the last admission round $j = 0$. δ captures the temporal effect of the interaction relative to some ex-ante specified baseline period, which we set to be the week before both admission rounds have passed to capture the entirety of demand prior the start of the academic year. We choose to include a pre-admission period of varying lengths to inspect pre-admission trends, with starting periods for $j = -24, -8$. Following Schmidheiny and Siegloch (2023) and Mense et al. (2023), we define I_t as a binned indicator capturing units outside of j. FE_t now includes weekly fixed effects together with year fixed effects. We estimate this model over the full sample, including the big three.

A key assumption is the random assignment of treatment, i.e., a student city listing around the admission period, but as we displayed in Tables 3 and 4, balancing on observables is challenging. As Swedish higher education expansion has favored larger urban areas, it is unlikely that the location of higher education institutions is randomly assigned. Our identifying assumption rests on the relative random assignment and variation in the admission round dates across years. A causal interpretation of these events rests on stable pre-trends between student and non-student cities.

The last admission round passes on August 4, 2015 (week 32) and August 3, 2016 (week 31) for all student cities, meaning that there is no variation in admission rounds between-city — only between years. The identifying variation in the event study estimation comes from this between-year variation in the timing of admission events between years, as with the calendar month specification. However, while the academic year starts on August 31, 2015 (week 36) and August 29, 2016 (week 35) in all student cities, the exact date can vary day-to-day between degree programs, usually by ±2 days from the formal academic year start date. This between-program variation is observable only to admitted students, even though it can create different lengths between the last admission round and the program-specific academic year start date.

In the following section, we test the sensitivity of our results to potential unaccounted heterogeneity in the timing of program-specific start dates within-year and between cities by artificially introducing variation in the passing of the last admission round and randomly allocating student cities into groups with different last admission round dates. We also conduct placebo tests to assess robustness to placebo treatment timing and placebo student cities.

The point estimates and their associated confidence intervals using the model in Eq. (5) are presented in Fig. 8. For a descriptive account of the pre-admission round window, see supplementary online appendix G. Four things are noteworthy. First, following the passing of the first admission round, there is little activity in monthly rent and almost a stabilizing effect. Second, following the second round of admission, there is seemingly no effect on rent, only for it to increase by 5.5 percent in week $j = 1$ and by 5.3 percent in week $j = 2$. There is persistence, as similar sized effects can be observed in week $j = 4$ and $j = 7$. Third, with 8 pre-treatment periods, the trend is considerably upwards sloping and would predict higher than observed effects following the passing of both admission rounds. This seems to particularly follow in the weeks leading up to the first admission round. Fourth, expanding the pre-treatment period stabilizes the trend and over 24 pre-treatment periods, while not entirely stable, the trend has a considerably flatter slope.

The upwards-sloping trend in the pre-admission period is perhaps unsurprising considering the relative difference of the big three compared to the rest of the sample, both in terms of region observables and market activity. This can also be further amplified by student cities like Uppsala and Umeå (Västerbotten county), which, as shown in supplementary online appendix F.2, also have higher listing density compared to the rest of the sample. A trend difference indicates that estimates from pooled event week regressions might attribute part of the upwards-sloping trend to the treatment. If so, the estimates would showcase positive bias and overestimate the treatment effect, given that the observed trend is positive.

The relatively stable trend over 24-pre treatment periods spurs us to assess average post-treatment effects, with the caveat that using the full sample most likely overestimates the treatment effect. Underlying trend differences between municipalities can be controlled for using municipality fixed effects, insofar as these differences are time invariant. Allowing for location-specific time trends can capture

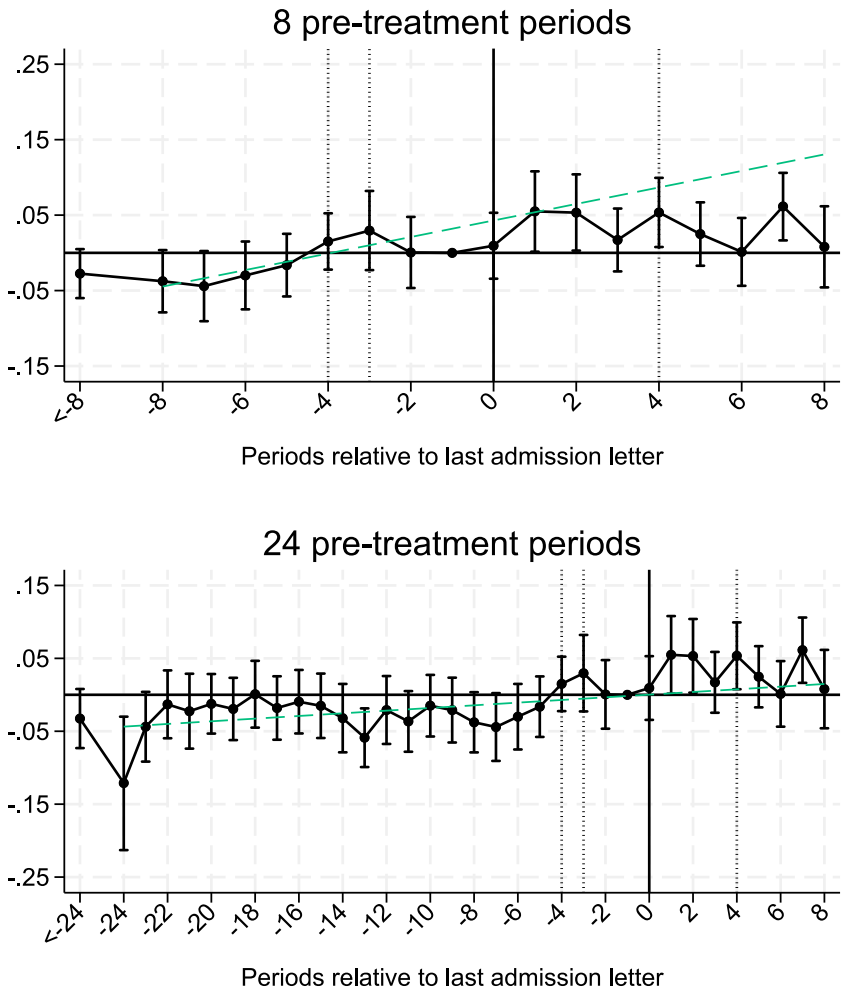

Fig. 8. Estimated pre-admission period trends of the log of monthly rent over varying window lengths.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. Reported are the 95% confidence intervals. Take note of the difference in scale on the y-axis. The first admission round is at week j=-4 (2015) and j=-3 (2016) (marked by the two dotted lines), the second and last admission round is at week j=0 (marked by the full line) and the academic year starts during week j=4 (marked by the last dotted line).

such phenomena given their dependence on time, which is why we fit municipality-specific monthly and quarterly linear time trends as a form of robustness.[16] We also assess robustness of the variation in the admission dates between years by controlling for year fixed effects.

The observed treatment effects of the interaction terms are reported in Table 6. We first estimate a barebones model in column 1 with municipality-district and week fixed effects. The observed effect is 8.28 percent and changes considerably to 5.4 percent in column 2 when we include listing characteristics. Fitting yearly fixed effects in column 3 has little effect on the estimate. From column 4 to column 7, we fit the municipality-district- and county-specific lower frequency time trends, again with only minor effect on our estimates. As can be seen in supplementary online appendix I.2, the post-admission indicator is negative in all but the barebones specification, implying that rent generally tends to decrease relative to the first half of the year. Overall, the post-treatment effects are similar ($\delta = 0.0537$; p<0.01) to the baseline model for July–September in Table 5 using calendar months ($\delta = 0.0463$; p<0.01).

We next exploit the net movement of students to municipality population in Table 7. This ratio varies across student cities and across years, while being equal to 0 in non-student cities. We similarly set the ratio to equal 0 in student cities during the pre-admission window, and going into effect the week when the second admission round passes. Estimating average treatment effect parameters between treated and untreated units under a parallel trends assumption on untreated potential outcomes is similar for continuous as for binary treatments (Callaway et al., 2024). While this allows us to exploit our continuous treatment under much of the same assumptions as our dichotomous treatment specification, the underlying trend difference from the big three might exaggerate the uncovered treatment effect. Changing to a continuous treatment indicator also changes the interpretation of the coefficients from average treatment effects to marginal treatment effects with changes in the treatment intensity. The net movement ratio at time t for municipality m is $Net_{m,t} = \frac{Students\ in-students\ out}{Municipality\ population}$ and is increasing in the number of students coming in and decreasing in the number of students going out and the municipality population.

As with the dichotomous variable, the barebones model in column 1 shows a considerably higher effect than the rest of the specifications. A one percentage point increase in the net movement ratio during the post admission period leads to a $0.01 \times 1.235 = 0.0124$ change in the log of monthly rent, or a $(e^{0.01235} - 1) \times 100 = 1.24$ percent increase in monthly rent. Controlling for listing characteristics and yearly fixed effects causes a one-percentage point increase in the net movement ratio to affect the log of monthly rent by $0.01 \times 0.767 = 0.0077$ units, or a $(e^{0.00767} - 1) \times 100 = 0.77$ percent increase in monthly rent. This is largely robust to the inclusion of lower frequency linear time trends.

[16] These time trends are on the district level for Stockholm, Göteborg and Malmö.

Table 6
Average effects in the post-admission period with dichotomous treatment indicator.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Municipality-specific		County-specific	
Dependent variable: Log of monthly rent	Barebones model	Listing characteristics	Calendar FE	Monthly trend	Quarterly trend	Monthly trend	Quarterly trend
Interaction	0.0828***	0.0540***	0.0537***	0.0526***	0.0517***	0.0516***	0.0517***
	(0.0173)	(0.0114)	(0.0114)	(0.0113)	(0.0112)	(0.0107)	(0.0107)
Observations	65,822	65,822	65,822	65,822	65,822	65,822	65,822
R-squared	0.210	0.596	0.600	0.602	0.602	0.600	0.600
Listing characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Monthly time trend	No	No	No	Yes	No	Yes	No
Quarterly time trend	No	No	No	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors clustered on the municipality-district level in parenthesis. The interaction consists of a dummy equal to one if the observation is in a student city, multiplied by a dummy for the post-admission period. The post-admission period indicator is defined as the week when the last admission round passes and runs for 8 weeks. See supplementary online appendix I.2 for estimated effects of covariates.

Table 7
Average effects in the post-admission period with continuous treatment indicator.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Municipality-specific		County-specific	
Dependent variable: Log of monthly rent	Barebones model	Listing characteristics	Calendar FE	Monthly trend	Quarterly trend	Monthly trend	Quarterly trend
Net movement ratio	1.235**	0.781**	0.767**	0.779**	0.731**	0.850***	0.828***
during post-admission period	(0.493)	(0.308)	(0.307)	(0.335)	(0.321)	(0.299)	(0.300)
Observations	65,822	65,822	65,822	65,822	65,822	65,822	65,822
R-squared	0.209	0.596	0.599	0.602	0.602	0.600	0.600
Listing characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Monthly time trend	No	No	No	Yes	No	Yes	No
Quarterly time trend	No	No	No	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors clustered on the municipality-district level in parenthesis. The post-admission period indicator is defined as the week when the last admission round passes and runs for 8 weeks. The continuous treatment is net movement to municipality population during the post-admission period. See supplementary online appendix I.3 for estimated effects of covariates.

The marginal effect of increased net movement ratios can have considerable effect on rents. In fact, a ten percentage point increase in the net movement ratio is associated with an increase in monthly rent by $(e^{0.0767} - 1) \times 100 = 7.97$ percent. Assuming that the total municipality population is only affected by the net movement of students, an increase in the average net movement ratio across all student cities by 10 percentage points would be associated with an increase in the base average monthly rent in the municipality of, for instance, Växjö by 442 sek (40 usd), or an increase in annual rent payments of 5306 sek (476 usd), for subtenants who sign their lease after the last round of admission has passed.

Robustness: Sensitivity to variation in treatment timing. We test the sensitivity of our results to potential heterogeneity in the timing of events within-year and between cities by artificially introducing variation in event start times and allocating student cities into different event start time groups. This variation is introduced by randomly assigning a share of all student cities to have the last admission round lagged and another share forwarded by the specified time intervals: ±2 days (a 5-day variation), ±4 days (a 9-day variation), and ±1 week (a 15-day variation). The remaining share of student cities that did not have their event start date lagged or forwarded retain the baseline event time, i.e., the actual passing of the last admission round in both 2015 and 2016. We allow the number of student cities included each of the three groups to vary and for each specified time interval, we run 500 iterations.

For the ±1 week specification, for instance, a share of $X_{lagged} = \frac{x_{lagged}}{(x_{lagged}+x_{forwarded}+x_{baseline})}$ student cities have the last admission round start one week earlier and a share of $X_{forwarded} = \frac{x_{forwarded}}{(x_{lagged}+x_{forwarded}+x_{baseline})}$ student cities have the last admission round start one week later, compared to the *de facto* last admission round date. The remaining share of student cities retain the actual last admission round date such that $X_{baseline} = \frac{x_{baseline}}{(x_{lagged}+x_{forwarded}+x_{baseline})}$. Naturally, $X_{lagged} + X_{forwarded} + X_{baseline} = 1$.

We pool the pre-admission and post-admission event weeks into to separate indicators of the form

$$\begin{aligned} ln(rent_{i,m,t}) = {} & \gamma_1\, preadmission_t^j + \gamma_2\, postadmission_t^j + \phi\, studentcities_m + \\ & \delta_1\, preadmission_t^j \times studentcities_m \\ & + \delta_2\, postadmission_t^j \times studentcities_m + \\ & FE_m + FE_t + x_i'\beta + u_{i,m,t} \end{aligned} \tag{6}$$

where $preadmission_t^j$ and $postadmission_t^j$ equal 1 if $j \in [-8,-1]$ or $j \in [0,8]$, respectively. This allows us to compare the average effect sizes for these different periods relative to observations captured by the binned indicator I_t. Robustness requires that the point estimates and t-values for the different temporal perturbations are scattered around the baseline estimates. We use a similar specification as in Eq. (5) to plot the separate weeks and their confidence interval distributions in supplementary online appendix H.

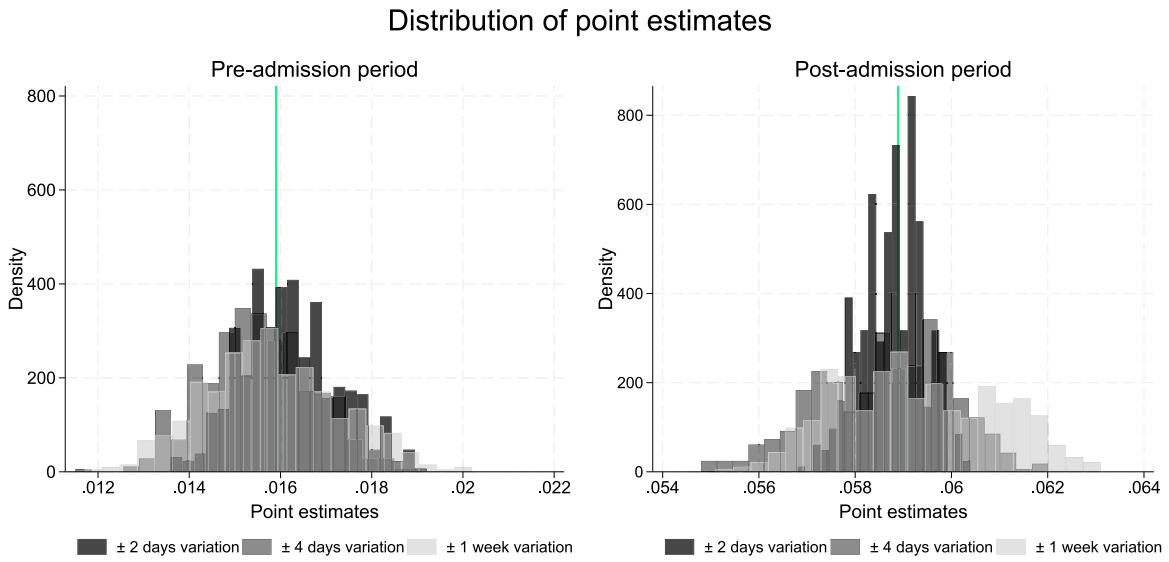

Fig. 9. Distribution of point estimates of randomized between-city variation over ±2 days (500 iterations), ±4 days (500 iterations) and ±1 week (500 iterations).
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. The green vertical line represents the point estimate without any artificial and random between-city variation. See supplementary online appendix H for the distributions of confidence intervals over the plotted event. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

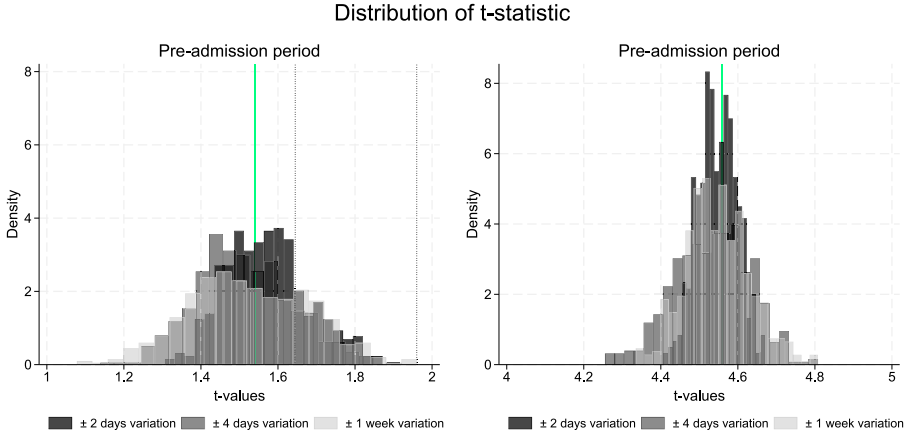

Fig. 10. Distribution of t-statistic for 500 iterations of randomized between-city variation over ±2 days (500 iterations), ±4 days (500 iterations) and ±1 week (500 iterations).
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. The green vertical line represents the point estimate without any artificial and random between-city variation. The dotted lines for the pre-admission periods represent a t-value of 1.645 and 1.96. See supplementary online appendix H for the distribution of confidence intervals over the plotted event. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figs. 9 and 10 display the distributions of average point estimates and t-statistics from 500 iterations of induced between-city variation during the pre- and post-admission periods from the model in Eq. (6). The baseline point estimates, estimated without any artificially induced between-city variation, is marked by the vertical green line.

In both periods, the variance of the point estimates increases as the magnitude of the induced variation widens. This underscores the sensitivity of the estimates to longer temporal perturbations upwards to ±1 week. The ±2-day perturbation has low variation and the point estimates are closely scattered around the baseline point estimates. In the present context where the academic year start date mostly varies by no more than ±2 days between degree programs, the impact of this heterogeneity should be minimal.

While no uncovered pre-admission period effect is statistically significant at the 5 percent or 1 percent level, approximately 15 to 25 percent of iterations indicate pre-admission point estimates significant at the 10 percent level, reflecting minor trends that align with those observed in Fig. 8. Using a similar specification as in Eq. (5) to plot the separate weeks and their associated confidence interval distributions, supplementary online appendix H demonstrates that the results are robust to ±2-day perturbations and largely robust to ±4-day perturbations. The higher density for ±2-day perturbations around the baseline point estimate in the post-admission period compared to the pre-admission period, coupled with consistently significant effects at the 1 percent level only post-admission, supports the notion that the treatment effect is driven primarily by changes occurring after admission and largely by between-year variation. This distinction reinforces the validity of the post-admission period as the primary window for treatment impact.

Robustness: Placebo testing for treatment validity. To test the validity of our results in the event week estimation, we conduct two placebo tests: (1) We preserve the time order but randomly assign which cities out of both the actual student cities and non-student cities are designated as placebo student cities ("treatment cities"), and (2) we preserve the actual treatment cities but randomly assign the passing of the last admission round. These tests use a specification similar to Eq. (6), where we define a pre-admission indicator as equal to 1 if $j \in [-8, -1]$ and a post-admission indicator as equal to 1 if $j \in [0, 8]$.

For the placebo treatment cities, we randomly select 24 of the 289 Swedish municipalities in the sample to serve as placebo student cities, iterating this process 500 times over the actual event window for 2015 and 2016. Since each iteration conditions on 24 randomly selected cities, the proportion of placebo student city observations can differ from the actual share (in our sample, approximately 63% of observations come from student cities). This variation in the share of observations that come from placebo student cities depends on whether the cities chosen as placebo student cities have relatively fewer or more observations. We try to account for this by conducting a large number of iterations (500).

For the placebo treatment timing, we restrict the sample to the period before the actual last admission round (up to week 32 in 2015 and week 31 in 2016) to avoid contamination from the real treatment effects. We randomly select two days, one from 2015 and one from 2016, and define the placebo start week as ±3 days around these dates.[17]

We further address the influence of larger student cities on the results. Larger cities have higher listing densities (see supplementary online appendix figure F.2) and including them seem to cause pre-trend differences (see Fig. 8). They may drive placebo results due to imbalances in observables (see Tables 3 and 4). To mitigate this, we repeat the placebo tests on a restricted sample excluding Stockholm, Västra Götaland, Skåne, Uppsala, and Västerbotten counties. This restricts the number of observations to 17,161 and covers approximately 40 percent of the entire net movement of students in the sample.

Figs. 11 and 12 show the distributions of point estimates and t-values for placebo treatment cities, while Figs. 13 and 14 do the same for placebo treatment timing. We wish to uncover low variance and null effects. For placebo treatment cities, a null effect suggests that the treatment effect is not spurious or driven by systematic differences between groups. For placebo treatment timing, a null effect validates the parallel trends assumption and indicates that groups evolved similarly before treatment.

We summarize average effects and t-values of all iterations in supplementary online appendix M.1, as well as the number of iterations showing significance at any conventional level in supplementary online appendix M.2. For placebo treatment cities, the point estimates in the pre-admission period are normally distributed and similar between the full and restricted sample. Post-admission, most placebo estimates fall below the actual treatment effect estimates, with the restricted sample showing higher variance. The full sample distribution has a U-shape, which likely indicates the sensitivity of the placebo samples to the inclusion of larger student cities. For the full sample t-values, the majority of placebo iterations are not statistically significant, although a notable 178 iterations are significant at the 10 percent level in the pre-admission period (130 at 5 percent and 64 at 1 percent). Comparatively, only 89 placebo iterations for the restricted sample are significant at the 10 percent level in the pre-admission period (52 at 5 percent and 13 at 1 percent).

For placebo treatment timing, the placebo point estimates are normally distributed in both periods and not centered around actual estimates. T-values for the restricted sample show few: 46 iterations pre-admission and 25 iterations post-admission are significant at the 10 percent level (pre-admission: 25 at 5 percent and 0 at 1 percent; post-admission: 18 at 5 percent and 0 at 1 percent). In contrast, the full sample shows significantly more variation, with 247 iterations pre-admission and 220-post admission significant at the 10 percent level (pre-admission: 194 at 5 percent and 104 at 1 percent; post-admission: 153 at 5 percent and 76 at 1 percent).

[17] We ran an additional 500 + 500 iterations where the placebo start week includes either the preceding or succeeding six days, instead of ±3 days from the randomly selected date. These specifications showed negligible differences to the specification used in this subsection.

4.4. Supply and demand response

Monthly rent and daily listing density over restricted sample. The placebo results raise concerns about the uncovered treatment effect when including larger municipalities, as iterations with placebo treatment timing yield high variance in the distribution of t-values (compared to the restricted sample) during both the pre- and post-admission period. When iterating using placebo treatment cities, it is clear that the distribution is heavily affected by larger student cities. In contrast, iterations using the restricted sample without larger cities for both placebo treatment timing and placebo treatment cities is normally distributed with low variance, and subsequently only a few placebo iterations show statistical significance on any conventional level. The restricted sample lends stronger support to the absence of pre-treatment trend differences and the absence of spurious treatment effects post-admission.

To address these concerns, we re-specify the analysis to focus exclusively on the restricted sample and thus comprising the remaining 16 counties in Sweden. This adjustment reduces the number of observations to 17,161, representing approximately 40% of the total net movement of students in the dataset. By narrowing the focus to this subset, we aim to provide a more robust test of the treatment effect under conditions where the assumption of parallel trends holds more plausibly.

We again rely on event weeks and identifying variation coming from variation in academic years' start times between years. We fit the model from Eqs. (3) and (4) for the restricted sample. As we are interested in analyzing the effect of percentage point changes in the net movement ratio on the dependent variables, we opt to utilize the raw count of average listing density (as opposed to its natural logarithm) for ease of interpretation in terms of absolute listings.

The results are plotted in Fig. 15. Compared to the plots in Fig. 8, the pre-admission period trend is substantially better behaved for the log of monthly rent, although still with positive slope. There is indication of anticipation effects leading up to the first admission round, followed by a downwards-sloping trend. The effect in monthly rent the week after the last admission round has passed is substantial and higher than what the pre-admission round trend would predict, reaching 17.5 percent and followed by an effect of 8.2 percent in the subsequent week. The persistence of the post-admission effect is similar to Fig. 8 using the full sample, but with more periods of overall significance.

Listing density has a more stable trend both before and after the first round of admissions. Daily listings decrease by 0.755 listings immediately during the terminal period and by 0.352 listings in the following period. This represents a decrease in the total average daily listing density of 29.6 percent ($\bar{Y}_{j=0}^{listings} = 2.554$) and 16.6 percent ($\bar{Y}_{j=1}^{listings} = 2.122$) respectively. Daily listing density then reverts back to pre-admission levels, with an additional negative effect in $j = 7$.

We pool our event study design to compare the period following the passing of the last admission round to the period before, for student cities compared to non-student cities. We focus on the ratio of net movement to municipality population, meaning that coefficients should be interpreted in terms of marginal changes of the dependent variable due to a change in the intensity of the ratio.[18]

[18] To ease comparison to the full sample estimates with a dichotomous treatment indicator in Table 6, we present the average post-admission treatment effects using a dichotomous treatment indicator of the restricted sample in supplementary online appendix N.1. For the restricted sample, the average post-admission treatment effect on rents is 0.102 ($p<0.01$) in the barebones model and 0.0516 ($p<0.05$) when also controlling for listing characteristics and calendar fixed effects. This is in line with the results when using the full sample, where the average post-admission treatment effects of 0.0828 ($p<0.01$) and 0.0537 ($p<0.01$) in the respective models.

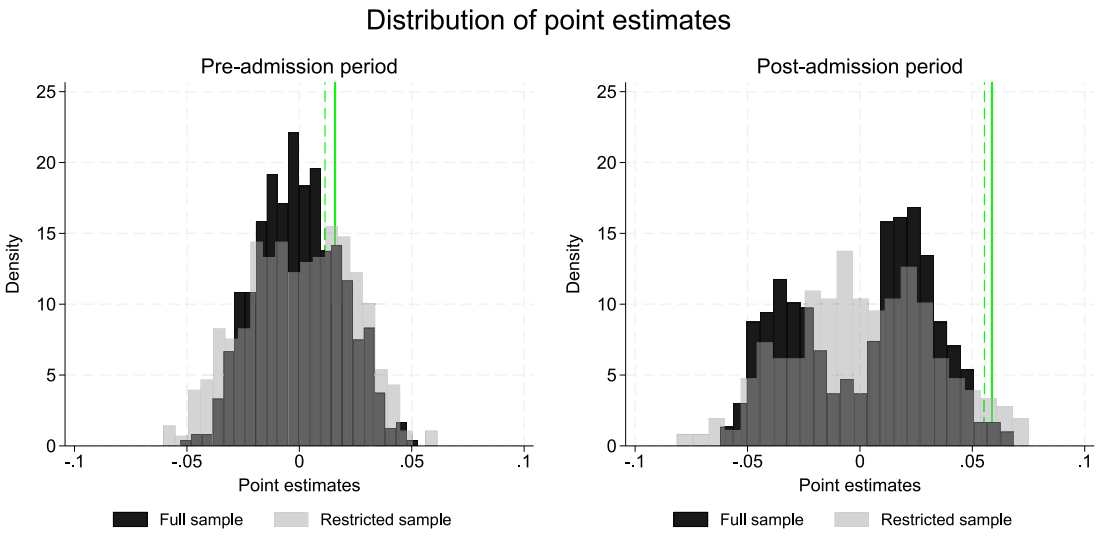

Fig. 11. Distribution of point estimates for the full sample (500 iterations) and restricted sample (500 iterations) with placebo treatment cities.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. The solid green vertical line represents the point estimate with the full sample and the dashed green vertical line represents the point estimate with the restricted sample. See supplementary online appendix M for summary statistics of the placebo iterations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

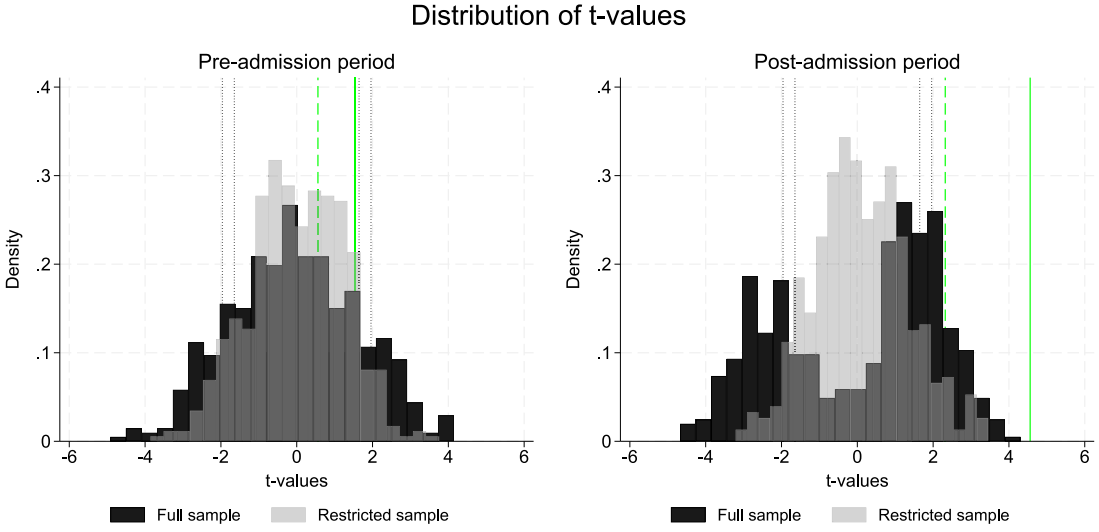

Fig. 12. Distribution of t-values for the full sample (500 iterations) and restricted sample (500 iterations) with placebo treatment cities.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. The solid green vertical line represents the point estimate with the full sample and the dashed green vertical line represents the point estimate with the restricted sample. The dotted lines represent a *t*-value of 1.645 and 1.96. See supplementary online appendix M for summary statistics of the placebo iterations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The effects on the log of monthly rent are presented in Table 8. Compared to the full sample, we uncover a similar but slightly higher effect on rents following a change in the net movement ratio during the post-admission period, with the model in column 1 showing a one percentage point increase in the net movement ratio leading to a $0.01 \times 1.951 = 0.01951$ change in the log of monthly rent, or a $(e^{0.01951} - 1) \times 100 = 1.97$ percent change in monthly rent — higher than the barebones model in Table 7 using the full sample, where a one percentage point increase in the net movement ratio led to a $(e^{0.01235} - 1) \times 100 = 1.24$ percent increase in monthly rent. This effect decreases when controlling for listing characteristics and time fixed effects in column 3, with a one percentage point increase in the net movement ratio leading to a $0.01 \times 0.977 = 0.00977$ change in the log of monthly rent, or a $(e^{0.00977} - 1) \times 100 = 0.98$ percent change in monthly rent. Municipality-specific time trends have a somewhat bigger impact on the point estimates compared to the estimates in Table 7, but the effect is nevertheless minor and in line with the full sample estimates.

Table 9 presents the estimates the net movement ratio on daily listing density. All models in the first three columns have very similar results, with a one percentage point decrease in the net movement ratio leading to a $0.01 \times 12.22 = 0.122$ decrease in daily listings for the model in column 3. This represents a decrease from the total average daily listing density of 5.9 percent ($\bar{Y}^{listings}_{\sum_{j=0}^{8}} = 2.058$). Fitting region-specific linear time trends lead to marginal changes in the point estimates and has no impact on statistical significance.

5. Discussion and conclusion

We have set out to assess the level of seasonality and dynamics of the Swedish market for long-term sublets. We leverage a unique data set of sublet listings between January 31, 2015 and January 18, 2017

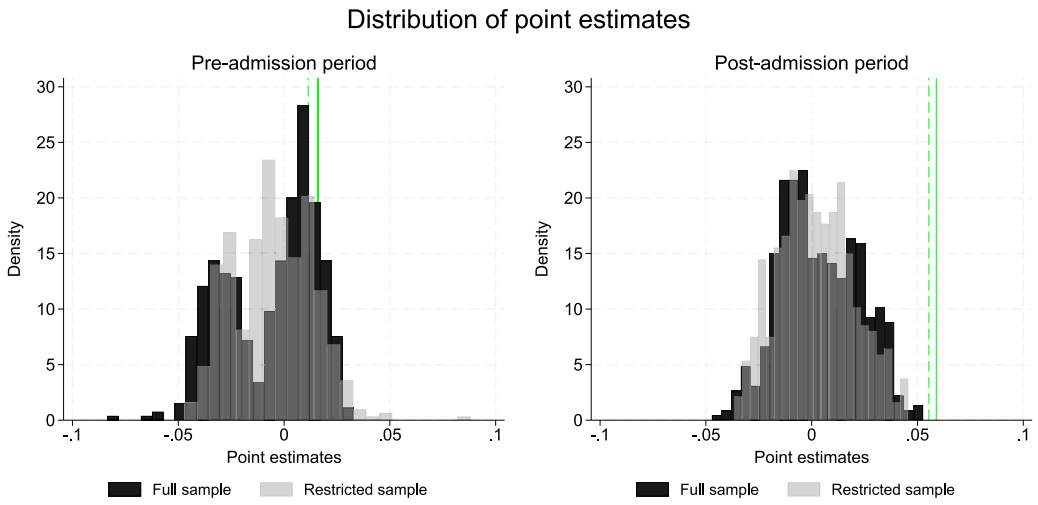

Fig. 13. Distribution of point estimates for the full sample (500 iterations) and restricted sample (500 iterations) with placebo treatment timing.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. The solid green vertical line represents the point estimate with the full sample and the dashed green vertical line represents the point estimate with the restricted sample. See supplementary online appendix M for summary statistics of the placebo iterations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

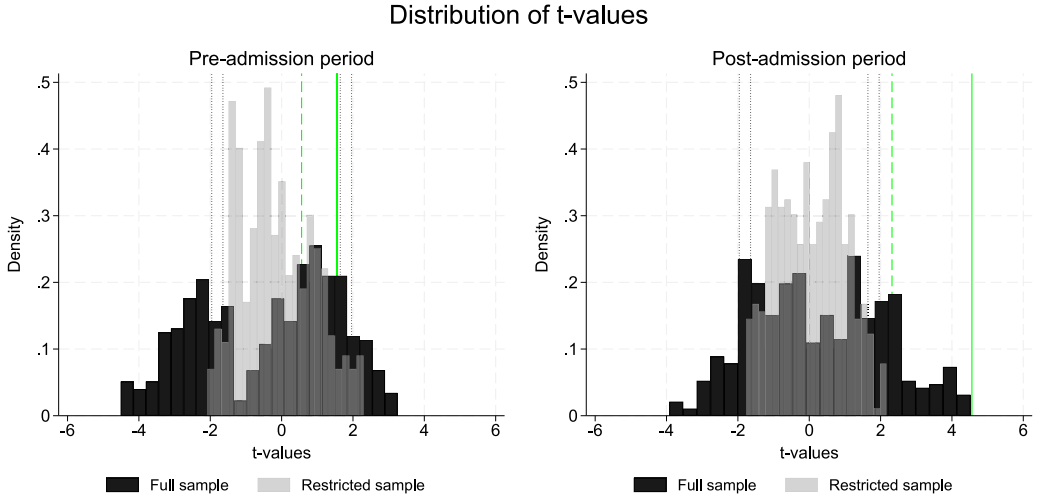

Fig. 14. Distribution of t-values for the full sample (500 iterations) and restricted sample (500 iterations) with placebo treatment timing.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. The solid green vertical line represents the point estimate with the full sample and the dashed green vertical line represents the point estimate with the restricted sample. The dotted lines represent a *t*-value of 1.645 and 1.96. See supplementary online appendix M for summary statistics of the placebo iterations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 8
Regression output of net movement ratios on the log of monthly rent for the restricted sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Municipality-specific		County-specific	
Dependent variable: Log of monthly rent	Barebones model	Listing characteristics	Calendar FE	Monthly trend	Quarterly trend	Monthly trend	Quarterly trend
Net movement ratio during post-admission period	1.951** (0.864)	0.975* (0.505)	0.977* (0.503)	0.875* (0.489)	0.841* (0.471)	1.002** (0.479)	0.983** (0.481)
Observations	17,160	17,160	17,160	17,160	17,160	17,160	17,160
R-squared	0.079	0.538	0.542	0.546	0.546	0.542	0.542
Listing characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Monthly time trend	No	No	No	Yes	No	Yes	No
Quarterly time trend	No	No	No	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors clustered on the municipality-district level in parenthesis. The post-admission period indicator is defined as the week when the last admission round passes and runs for 8 weeks. The continuous treatment is net movement to municipality population during the post-admission period. See appendix I.4 for estimated effects of covariates.

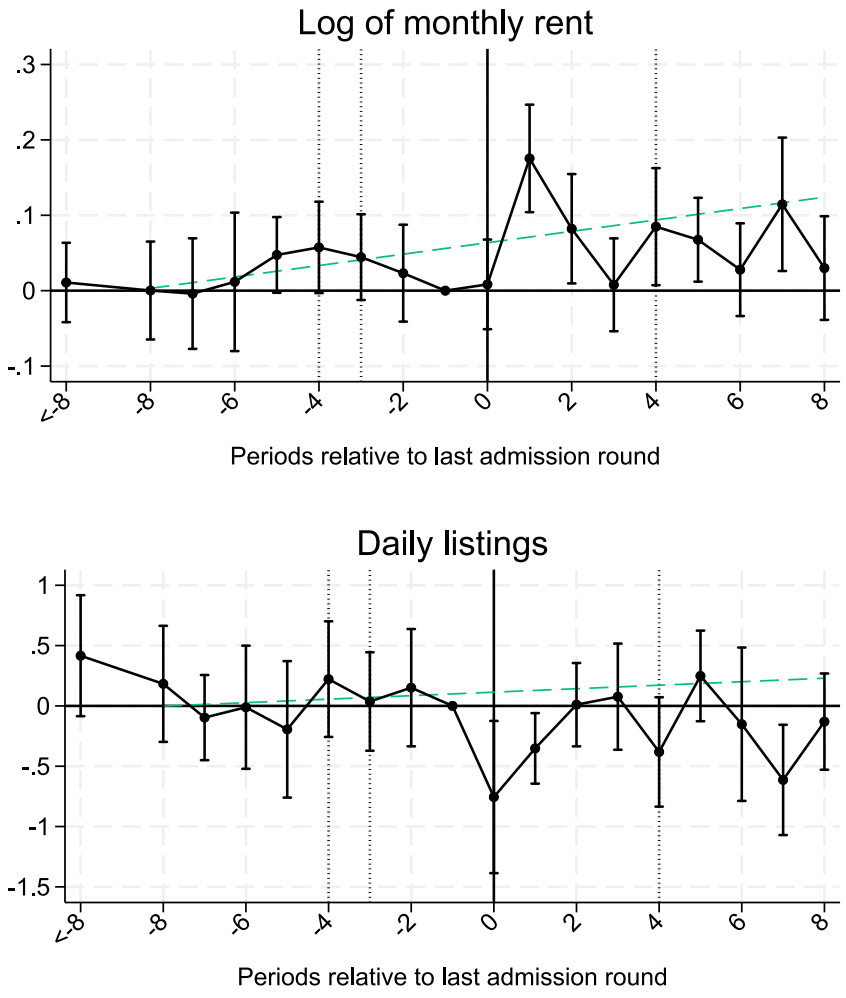

Fig. 15. Estimated pre-admission period trends for the restricted sample.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. Reported are the 90% confidence intervals. Take note of the difference in scale on the *y*-axis. The first admission round is at week j=-4 (2015) and j=-3 (2016) (marked by the two dotted lines), the second and last admission round is at week j=0 (marked by the full line) and the academic year starts during week j=4 (marked by the last dotted line).

Table 9
Regression output of net movement ratios on daily listing density for the restricted sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Municipality-specific		County-specific	
Dependent variable: Daily listing density	Barebones model	Listing characteristics	Calendar FE	Monthly trend	Quarterly trend	Monthly trend	Quarterly trend
Net movement ratio during post-admission period	−12.47** (4.998)	−12.23** (4.932)	−12.22** (4.930)	−13.84** (5.666)	−13.40** (5.355)	−11.83** (4.909)	−11.88** (4.911)
Observations	17,160	17,160	17,160	17,160	17,160	17,160	17,160
R-squared	0.330	0.333	0.333	0.343	0.343	0.336	0.337
Listing characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Monthly time trend	No	No	No	Yes	No	Yes	No
Quarterly time trend	No	No	No	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors clustered on the municipality-district level in parenthesis. The post-admission period indicator is defined as the week when the last admission round passes and runs for 8 weeks. The continuous treatment is net movement to municipality population during the post-admission period. See appendix I.5 for estimated effects of covariates.

for the entirety of the country to compare student cities to non-student cities. We find no statistical difference in rents during the first half of the year in student cities, but uncover considerable seasonality ignited by a sharp and persistent increase in rents of 6.1 percent in August relative to January. Listing density in student cities increases drastically until May but is completely offset by September, reaching negative levels throughout the rest of the year.

We hypothesize that the start of the academic year drives sublet demand as students become prospective subtenants. Rents increase by 4.6 percent over calendar months and by 5.4 percent over event weeks in student cities relative to non-student cities in the post-admission

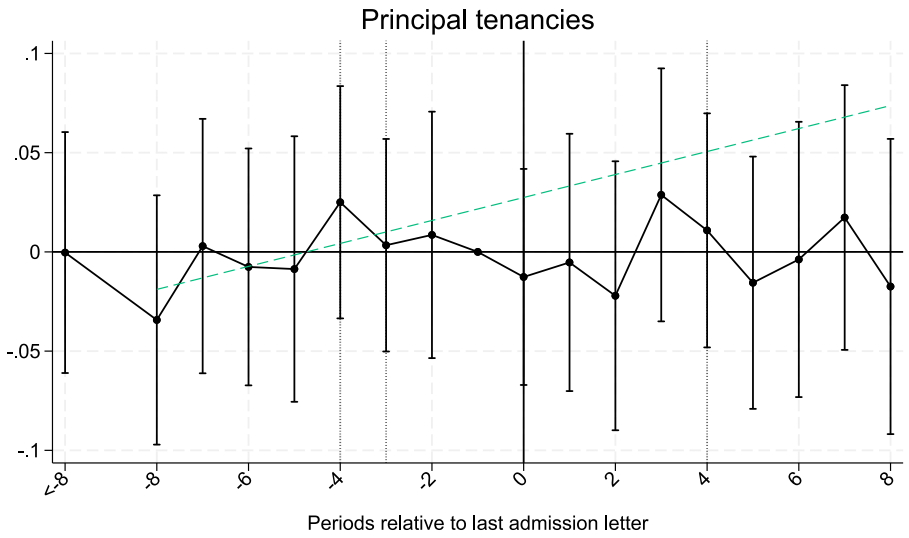

Fig. 16. Event study plot for principal tenancies in Stockholm county and Uppsala municipality over sample period.
Note: Heteroscedasticity-robust standard errors are clustered on the municipality-district level. Reported are the 95% confidence intervals. The plot concerns principal tenancies allocated through the Stockholm housing queue (Stockholms Bostadsförmedling AB) for student cities in Stockholm county and Uppsala municipality, against a control group of non-student cities in Stockholm county. The plot controls for the log of square meters, the log of room size, the number of rooms, the type of dwelling, the number of years in queue, the floor of the dwelling in the apartment building, the successful applicant's age, landlord ID and a first time rental indicator. The first admission round is at week j=-4 (2015) and j=-3 (2016) (marked by the two dotted lines), the second and last admission round is at week j=0 (marked by the full line) and the academic year starts during week j=4 (marked by the last dotted line).

window. However, the relative weight of larger student city municipalities casts some doubt on the estimates, which is why we assess a more robust subsample with arguably more comparable student and non-student cities. We uncover effects of similar magnitude, with rents rising by approximately 5.2 percent relative to non-student cities in the post admission window. In terms of ratios, a one percentage point increase in the net movement of students relative to municipality population causes monthly rents to rise by 0.77 percent over the full sample and by 0.98 percent over the restricted sample. For the restricted sample, the number of daily listings decrease by 0.122 listings following a percentage point increase in the net movement ratio, representing a 5.9 percent decrease in total average daily listing density.

In other words, we find that sublet rents react strongly to sudden demand shocks in student cities and that this persistence is sticky, which seems to be able to explain some of the observed seasonality on the market for long-term sublets. Principal tenants do not experience such sharp increases in rent following the start of the academic year: using an auxiliary data set over principal tenancies allocated through the housing queues in Stockholm county and Uppsala municipality, we plot the same 8-week pre-admission window for student cities and non-student cities over principal tenancies in Fig. 16. As is apparent, there are no significant pre-trend nor post-admission effects. Principal tenants are completely protected from the sudden fluctuations in rents during periods of high demand on the market for long-term sublets. Our study shows that prospective subtenants cannot afford this luxury — following the last admission round, rents increase and the listings decrease.

This can potentially reinforce the insider-outsider-dilemma, where "insider" principal tenants enjoy low-to-negative monetary costs of rent control, while "outsider" subletters face considerable rent level fluctuations (Lindbeck, 2016; Riksbank, 2019). In a sense, the Swedish rental market regulations achieve their goal of staving off sudden and drastic rent increases on the principal market. However, the average successful principal tenant immediately following the start of the academic year is 37 years old in our sample, while the average age at graduation is 28 years old according to Statistics Sweden. This suggests that it is not students who are the beneficiaries of the Swedish rent regulation — at least in Stockholm. Considering that rent control and rental market regulations are making their way back into policy debate and are often motivated as tools for fairness, to equalize access to housing across socioeconomic status, our results suggest that policy makers should be aware that rent regulation policies targeting a specific segment, no matter how fair and righteous such interventions might sound, can have adverse effects on other rental market segments and on the associated tenants. Future research should aim to investigate seasonality and dynamics of markets for long-term subletting in other countries and institutional contexts, to aid in the understanding of how such markets function and how their dynamics can affect the people that utilize them.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Microsoft Copilot in order to assist with table formatting in Latex. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhe.2025.102049.

Data availability

Data will be made available on request.

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