DISCUSSION PAPER SERIES

IZA DP No. 16726

Housing Costs, College Enrollment, and Student Mobility

Johannes Goehausen
Stephan L. Thomsen

JANUARY 2024

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16726

Housing Costs, College Enrollment, and Student Mobility

Johannes Goehausen
Leibniz University Hannover

Stephan L. Thomsen
Leibniz University Hannover, ZEW and IZA

JANUARY 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Housing Costs, College Enrollment, and Student Mobility*

We study the effects of rental price changes on college enrollment rates. We exploit cross-district variation in the size and timing of local rental price booms in Germany during the 2010s. A one standard deviation increase in apartment rents decreased per-capita college enrollment by 1.1 percentage points on average. The effect was driven by first-year students moving long distances and was more pronounced in less densely populated locations. Housing costs—the largest component of students' expenditures and an important location factor— have contributed to the slowdown in higher education expansion and reduced the skill-binding effect of universities, exacerbating regional inequality.

JEL Classification: I23, R21, R31

Keywords: college enrollments, housing market, apartment rents

Corresponding author:
Johannes Goehausen
Leibniz University Hannover
Institute of Economic Policy
Königsworther Platz 1
30167 Hannover
Germany

E-mail: goehausen@wipol.uni-hannover.de

* We are grateful to participants of the 5th Workshop for Young Scientists on "Applied Economics" (2023) and of the annual meeting of the European Society for Population Economics (2023) for their most helpful comments and discussions. We also thank the FDZ Ruhr at the RWI—Leibniz Institute for Economic Research for providing the RWI-GEO-REDX (2008-06/2022, v9), doi:10.7807/immo:redx:v9, and Sandra Schaffner and Patrick Thiel for providing a special evaluation of the RWI-GEO-REDX on a quarterly basis. We further thank Christian Oberst for providing the raw data of the IW Student Housing Price Index and the Studierendenwerk for providing older issues of their reports "Student Housing in Germany Statistical Overview" and "Student Service Organisations Facts and Figures".

1 Introduction

Over the past two decades, many countries have experienced significant housing market booms (Knoll et al., 2017), leading to a shortage of affordable housing, especially in urban areas (Wetzstein, 2017). Due to their high location demand for these areas but relatively low incomes, college students are considered to be disproportionately affected. This issue has been reported in various countries, such as the US (The Washington Post, 2022), the UK (The Guardian, 2022), France (Le Monde, 2022), and Germany (SWR, 2022). As a result, policymakers worry that potential students are deterred from pursuing college or are forced to compromise on their preferred institutions or fields of study.[1] First, as low-income students are more sensitive to college costs (e.g., Dynarski et al., 2022), this would exacerbate existing inequalities in educational attainment and limit social mobility. Second, because a substantial share of students stay in the college region after graduation (e.g., Winters, 2020), a lower inflow of students relative to other regions could lead to lower skill supply in the future, diminishing long-term growth potential and increasing regional disparities in income and well-being.

In this paper, we investigate the elasticity of college enrollment to a change in rental prices at the regional level. To do so, we focus on Germany over the past decade, which is an ideal case to study this question: First, there was a significant, unprecedented, and spatially divergent boom in the housing market (Brausewetter et al., 2023). On average, between 2010 and 2019, purchase prices rose by 70 percent and rental prices by 43 percent (see Panels A and B in Figure 1; Deutsche Bundesbank 2022). Typical student apartments in popular university cities experienced an increase of almost as much on average (+37%) (see Panel C in Figure 1; Oberst and Voigtländer 2018; MLP SE 2022). This exceeded both inflation (+13%) and the increase in the average amount of BAföG (+18%), the public (but rarely used) financial aid program for students.[2] Second, since there are essentially no tuition fees in Germany, housing costs account for the largest proportion of students' total expenses (46% in 2021; Kroher et al. 2023). For this reason, and due to the considerable heterogeneity across regions (e.g., 186 euros for a typical room in a shared flat in Chemnitz vs. 545 euros in Munich; MLP SE 2022), students in Germany are likely to be sensitive to changes in apartment rent. Third, and relatedly, the higher education system is much less selective than in the Anglo-American context, so there are much less significant differences in expected returns across particular schools and locations that could compensate for differences in housing costs.[3]

[1] For example, the HUD's Office of Policy Development and Research warned in 2015 that a "'sticker shock' from high prices can deter [low-income] students from applying [to college] even when they are academically qualified" (PD&R, 2015, p. 4). Similarly, in 2023, the German government announced a program to support new construction of student housing. The German Student Union welcomed this and noted "the choice of university location should not depend on whether students can afford the rent locally" (Deutscher Bundestag, 2023, p. 2).

[2] The BAföG is a means-tested financial aid program for students from low-income families in Germany. It is granted half as an interest-free, repayable loan and half as a non-repayable grant. The maximum amount per month is 934 euros (as of February 2023). However, only a very small share of students (18% in 2016; Middendorff et al. 2017) (can) take advantage of it.

[3] For example, Chetty et al. (2020) report for the US that Ivy-Plus graduates earn more than twice as much as the average college graduate. In Germany, however, graduates from the top universities earn only slightly more

< Insert Figure 1 here >

Acknowledging the specific institutional context of Germany, we take a human capital perspective and view college-going as an investment decision, where individuals weigh the expected returns against the associated costs and compare different available options. An increase in housing prices should therefore primarily represent a shock to students' direct costs of college-going. *Ceteris paribus*, we expect students to respond at different margins: First, higher housing costs may lead to a decision not to study in a particular location and, therefore, to lower enrollment rates at the regional level (extensive margin). Second, within specific locations, students may follow different adaptation strategies at the intensive margin: reducing the study length (study compression) or changing the choice of institution or field of study, e.g., in favor of institutions/fields that offer higher expected returns. Even if the effects should be negative (if at all), the elasticity of enrollment rates to rental prices is unclear. It may also vary for different population subgroups, such as university or university of applied sciences (UAS) students, e.g., due to different mobility.

To study the effects of apartment rents on college enrollment rates, we rely on aggregated administrative student statistics from the Federal Statistical Office of Germany (Destatis). These data provide a complete record of all enrollments at publicly acknowledged institutions of higher education in Germany (hereafter referred to as college enrollments), including universities and universities of applied sciences (UAS). We combine these data with quarterly data on the development of quality-adjusted apartment rents from the RWI-GEO-REDX provided by the FDZ Ruhr at the RWI (Schaffner et al., 2022b) at the level of administrative districts.[4] Although students search for specific types of housing (e.g., rooms in shared flats), we can show that annual growth rates in rental prices for all apartments and for student apartments are reasonably correlated and that rental ads in student cities show a spike in hits just before the start of the winter term.

To estimate causal effects, we follow the literature on the US housing market boom (Charles et al., 2018; Ferreira and Gyourko, 2021) and identify structural breaks in the development of apartment rents within a given district. These breaks represent a source of exogenous variation, allowing us to use them as an instrument for the total change in apartment rents during the main boom period from 2010 to 2019.[5] In the year after the structural break, rental price growth is 4.2% higher unconditionally, and 3.9% higher after accounting for year fixed effects. This elevated price growth persists in the subsequent years. Moreover, we provide evidence that the sizes of the structural breaks are correlated with common indicators of a housing market bubble, such as the price-to-rent gap or the price-to-income gap. We further show that the timing of the breaks does not coincide with shocks to key fundamental supply and demand factors, such as population (e.g.,

than the average (StepStone, 2020). While these numbers are unadjusted for student composition and purely correlational, there is also substantial causal evidence of a selective college premium for the US (see Lovenheim and Smith 2022 for a recent review) but not for Germany (Lang and Schwabe, 2023).

[4] Administrative districts correspond to NUTS-3 regions at the EU level and are comparable to US counties.

[5] In recent years, apartment rents have risen even faster. However, because of the COVID-19 pandemic and its confounding effect on college enrollment, we do not consider the most recent period.

the immigration in the wake of the 2015 refugee crisis), income, employment, or building permits. Instead, the structural break in apartment rents coincides with an increase in the price-to-rent ratio, suggesting that a prior and over-proportional increase in apartment purchase prices is being passed through to rental prices. To validate our findings, we also exploit both the timing and the size of the structural breaks in a difference-in-differences (DiD) and an event study setting. By relaxing the exogeneity assumption, we can identify reduced-form estimates of the effect of sharp changes in apartment rents, regardless of their source, be it speculative activity or shocks to labor demand or amenities.

We find that the housing market boom significantly reduced college enrollment within the average district. In the 2SLS specification, we estimate that a one percent increase in apartment rents reduced the 5-year average per-capita enrollment by –0.08. Thus, a one standard deviation increase in rental prices (+14%) leads to a decrease in the enrollment rate by 1.1 percentage points. This effect is robust to alternative definitions of the outcome variable and the instrument as well as to placebo tests. Reassuringly, the DiD design yields similar estimates, which are also robust to basic time-varying controls, such as population or skill level. Looking at apartment and house *purchase* prices (instead of apartment rents), we consistently find no effects, suggesting that the negative enrollment effects are plausibly driven by increased direct costs of studying rather than opportunity costs. This is in line with the—compared to the US (Charles et al., 2018)—low, only average job creation in construction and in the related FIRE sector (see Panel D in Figure 1).

We do not observe responses of students at the intensive margin in terms of study duration. However, we find that the effects are clearly driven by first-year students at universities (and thus by corresponding degrees and areas of study, such as teaching and state exams and natural sciences, respectively). We explain this by differences in mobility, as universities tend to have a larger catchment area than UAS. In fact, we find that local students are not affected by the rental price increase—possibly due to compensation by staying with their parents. In contrast, the effects appear especially for students who graduated from high school outside the state of the higher education institution or more than 200 kilometers away. Similarly, we also report negative effects for international students. Our results further suggest that apartment rents reduced enrollment rates particularly in medium-sized urban districts (densely populated but not city districts) and in more rural areas. These areas offer fewer consumption amenities than the top university cities, making them arguably more susceptible to rental price increases.

Assuming all else equal, and scaling the effect by the average total rental price increase over our observation period (+27%), we estimate in a simple back-of-the-envelope calculation that college enrollment rates in the average district are 16% lower in 2019 than in the counterfactual of no price boom. However, since the effects are driven by mobile students, this does not necessarily imply also lower *aggregate* enrollment. For instance, marginal students could enroll elsewhere or pursue outside options. Regarding the latter, we do not find evidence for an increase in applications for vocational education and training, but some evidence of increased employment, which, however, plays only a minor role as a permanent career path for college-eligible school graduates in Germany.

This paper contributes to at least two strands of related literature: First, Lovenheim (2011), Lovenheim and Reynolds (2013), and Charles et al. (2018) study the effects of the US housing market boom on college enrollment decisions focusing on two alternative mechanisms. Lovenheim (2011) and Lovenheim and Reynolds (2013) show that the house price boom increased college enrollment by raising family wealth. On the other hand, Charles et al. (2018) find that higher housing demand reduced college enrollment by increasing employment prospects for individuals without a college degree in construction and related services, thereby raising the opportunity cost of attending college. In return, our results suggest that in a different institutional setting, a housing market boom affects college enrollment decisions primarily through a third channel, namely the *direct* cost of attending college. In general, the impact of housing price booms may thus depend on the housing-related share in the ratio of direct and indirect costs of study.

Second, we complement an extensive literature on the effects of housing prices on (labor) mobility. This is studied mainly from the perspective of lock-in-effects of homeownership, leading to decreased mobility (e.g., Ferreira et al., 2010; Goetz, 2013; Foote, 2016; Brown and Matsa, 2020; Bernstein and Struyven, 2022). As one of the exceptions, Bauer et al. (2019) study the determinants of interregional migration more broadly, with housing costs as one of many considered factors. They find a significant but relatively small effect on internal migration flows. A similarly comprehensive approach can be found in the literature on university choices of students, with most studies not considering housing costs (Hemsley-Brown and Oplatka, 2015) and one finding a negative relationship with location choice (Sá et al., 2012). To our knowledge, we are the first to provide causal evidence on how students' location choices are affected by rental prices.

The identified changes at the margins of whether, where, and what to study have important implications for social and regional inequality. Attending college provides large private returns to higher education (e.g., Gunderson and Oreopolous, 2020), with heterogeneity by major (e.g., Altonji et al., 2012; Kirkeboen et al., 2016) and quality of the institution (e.g., Hoekstra, 2009; Deming et al., 2016). Thus, the decision not to study at a distant university is likely to result in second-best options associated with potentially lower returns. However, as it is students from higher socio-economic backgrounds who have a higher propensity to move (Schneider et al., 2017), our results do not necessarily imply a worsening of social inequality. At the regional level, attracting students plays a crucial role in educating and retaining the future stock of skilled workers (e.g., Winters, 2020; Berlingieri et al., 2022; Carneiro et al., 2023). Since we find that the negative effects are primarily driven beyond very large urban areas, these regions are likely to have difficulties attracting high-skilled workers anyway, which may be exacerbated by the housing price boom. Finally, at the policy level, our findings point to the provision of affordable housing as an important location factor valued by students, which seems to be even more relevant in times of declining enrollment numbers.

The remainder of this paper is structured as follows: After discussing the institutional context (Section 2), we provide a brief description of our data sources (Section 3). Then, we discuss the empirical strategy (Section 4). Section 5 presents our results, including the heterogeneity of effects, mechanisms, and robustness checks. Section 6 concludes.

2 Institutional Context

2.1 The Housing and Living Situation of Students

We start by describing the housing and living situation of students and their evolution over time. This serves to understand the institutional context of Germany better and to identify potential channels for compensation effects.

In terms of location, about 60 percent of all first-year students attend college in the same federal state where they obtained their higher education entrance qualification, about 30 percent in the same labor market region, and less than 20 percent in the same district (see Panel A in Appendix Figure A-1). Overall, these migration patterns have remained relatively stable (–2 percentage points decrease in the share of home-state students between 2010 and 2019). This is also the case for most subgroups shown; only East Germany experienced a sharp decline in the share of home-state students, reflecting the substantial influx of West German students during this period (see Panels B-G in Appendix Figure A-1). Thus, in 2019, only about 35 percent of students graduated in the same federal state as their higher education institution, compared to about 60 percent in West Germany.

Students in Germany have four main housing options: According to the DZHW Social Survey, 38 percent of students in 2016 lived in a private apartment—either alone (17%) or with a partner (21%). 30 percent lived in a shared flat, 20 percent lived with their parents, and 12 percent lived in a student residence hall. Compared to 2009, there were some shifts in housing situations, with fewer students living with their parents (–3 percentage points) and more students living in shared flats (+4 percentage points) (Middendorff et al., 2017). At first sight, this trend contrasts with the increase in apartment rents but may well reflect changes in students' preferences.[6] The observed trends are also present for different subgroups, such as region, type of institution, or gender, albeit starting from different levels (see Panels B-G in Appendix Figure A-2).

Students living on their own currently spend an average of 393 euros per month, or 46 percent of their total expenses, on housing (including utilities) (Kroher et al., 2023). This is about forty percent more than in 2009 (Middendorff et al., 2017), exceeding both inflation and the increase in BAföG (see again Figure 1). There is also great heterogeneity in housing costs by type of housing and location (2021): On average, a typical student room in a shared flat (20 m^2) currently costs about 357 euros, including utilities, a standard single apartment (30 m^2) about 521 euros, and a room in a residence hall 267

[6] More recent data from the 2021 cohort suggest that this trend may has reversed, although the wave is not fully comparable with previous waves due to a change in the reporting scheme (Kroher et al., 2023).

euros. These prices vary widely and range from 186 (min) to 545 euros (max) (room in shared flat), from 224 to 787 euros (single apartment), and from 212 to 354 euros (room in residence hall) by location, respectively (Deutsches Studierendenwerk, 2020; MLP SE, 2022).

To finance their studies, students use a variety of sources: On average, 51 percent is parental support, 26 percent own earnings, and 12 percent BAföG. However, the income composition depends strongly on whether one works (68% in 2016) and/or receives BAföG (18% in 2016), with the proportion of BaföG recipients declining for years (–4 percentage points compared to 2009) (Middendorff et al., 2017). It is important to note that since BAföG is the same in all regions, it does not compensate for regional differences in housing and living costs, nor are these differences fully compensated for by income differences (own earnings and parental support) (Middendorff et al., 2017).[7] Given the variation in housing affordability across regions, it seems plausible that some students are sensitive to housing prices when deciding where to study. Indeed, about 60 percent of students report that "cheap rent" was a strong motive for their choice of living situation (Middendorff et al., 2017).

Besides variation in housing affordability, there is also great heterogeneity in the level of competition for affordable housing, depending on the availability of suitable apartments, places in student residence halls, and the number of students per population (see Appendix Table A-2). Although this should be reflected in prices to some extent, these supply differences are still worth considering. The competition is particularly intense in West Germany and in large cities. In general, the situation on the public (or subsidized) student housing market has also worsened significantly in recent years, as the higher education expansion has not been met by a significant increase in housing supply. For example, the total number of units in student residence halls increased by only six percent between 2010 and 2019, while the number of students increased by more than 30 percent over the same period. This led to a decline in the share of places in residence halls per student by about 20 percent, from 12% to 9% (see Panel A in Figure 2).

< Insert Figure 2 here >

In contrast, the number of residential buildings per capita and the number of single apartments expanded slightly on average over the period considered, relaxing the private market in terms of actual supply. However, this varies greatly from region to region and also applies less to the actual available supply on the market, measured in the number of advertisements per capita and the time of advertisements on the market (TOM). As shown in Panel B of Figure 2, both the number of ads per capita and the TOM decreased over the period considered. Overall, and in line with the observed price increases, the housing market tightened considerably, especially for students.

[7]As a result, the BAföG housing allowance is just enough for a room of 11 square meters in a shared flat in Munich but three times as much in Chemnitz (MLP SE, 2022).

2.2 Admissions and Funding of Higher Education in Germany

According to the German constitution, access to and choice of higher education institutions is free and open to all who meet the formal requirements. With a few exceptions, this means having a higher education entrance qualification (*(Fach-)Abitur*). However, institutions may restrict admissions if demand for specific programs exceeds capacity. This applies to about 40 percent of all bachelor's programs, while the remaining 60 percent are open admissions (HRK, 2021). Admission restriction is mainly based on a system called Numerus Clausus (NC), which sets specific limits on the number of students who can be admitted to each program, taking into account the capacity of the university (based on the endowment with teaching staff and facilities) and the demand for the program (projected by past demand). The NC is set each year by each university and program and is often based on high school GPA. However, in some high-demand fields, such as medicine, pharmacy, and dentistry, the admissions process is entirely centralized. For these programs, students can list five preferences for study locations and are then allocated throughout Germany in a highly selective process, primarily based on high school GPA and the results of a separate entrance examination. We will exploit this institutional difference in admissions for a robustness check in Section 5.4.

In Germany, the higher education system is predominantly publicly funded. The federal states provide the largest portion of total funding (71% at higher education institutions (without clinics) in 2020) as so-called basic funding to cover operating expenses and investments (Destatis, 2022). The amount is determined primarily through complex negotiations between the university and the respective state ministry, taking into account factors such as the number of enrollments, students within the regular study duration, and graduates, as well as weaker criteria such as subjects offered and (perceived) labor demand.

Overall, higher education funding in Germany is reasonably balanced in terms of incentives. On the one hand, having more students can increase a university's funding in the future. Similarly, funding cuts may be imminent if available study places are not filled. On the other hand, having too many students can also strain the institution's resources in the short term and negatively impact quality, so universities aim to strike a balance. In the context of our analysis, this means that an exogenous reduction in enrollment will result in open study places in the short run, but may lead to an adjustment in study places and thus to a cut in funding in the long run.

2.3 The Higher Education Expansion

During our observation period, Germany underwent several reforms and changes in its higher education system, which led to generally rising college enrollment rates but also to discontinuities in some years. In the following, we present key facts about the aggregate developments in the higher education system to assess potential confounding effects for identifying the causal impact of apartment rents.

Beginning a few years before the housing market boom studied in this paper (2010-2019), the number of first-year students increased from 356,000 (2005) to 519,000 (2011)—an increase of more than 40 percent within six years (BMBF, 2023). To some extent, this was due to one-off effects, such as the G8 reform[8] that led to several double high school graduation cohorts between 2007 and 2014 and the abolition of the military conscription for men in 2011. Nevertheless, enrollment rates remained high in the following years until a sharp drop during the COVID-19 pandemic, which we therefore exclude from our analysis.

Furthermore, the higher education expansion cannot be explained, or only to a limited extent, by the introduction of the Bologna reform, which, in contrast to other countries, was found to have little effect on aggregate college enrollment decisions in Germany (Kroher et al., 2021). However, the expansion closely matches the increase in higher education qualification rates that occurred a few years earlier (BMBF, 2023). First, the share of an age cohort that acquires the formal requirements for enrolling in higher education increased from 37% (2000) to 54% (peak in 2012). Then, a few years later, the share of an age cohort that actually enrolls in higher education also increased, from 33% (2000) to 58% (peak in 2014) (see Appendix Figure A-3).

At the regional level, however, there is substantial variation in the extent of this higher education expansion. While the median district experienced an increase of about 45 percent between 2005 and 2010, reaching a sort of plateau with slightly declining numbers thereafter, the top ten percent of districts saw an increase of more than 150 percent that lasted until the end of our observation period in 2019. In contrast, the bottom ten percent showed some increases around 2010-2014, but ended up with an overall decline (–6%) (see Panel A in Figure 3).

< Insert Figure 3 here >

Panel B of Figure 3 offers a potential explanation for these different trends in college enrollment rates across regions, which we will explore in this paper. There appears to be a small negative relationship between the total change in apartment rents from 2010 to 2019 and the total change in first-year enrollment per capita. Of course, this pattern could be driven by latent factors, such as shocks to amenities or labor demand. In our analysis below, we therefore aim to isolate the direct causal effect of apartment rents on enrollment rates.

3 Data

We combine data from multiple sources to identify the effects of housing prices on college enrollment at different margins and levels. Appendix Table A-1 describes in detail all the

[8]The G8 reform reduced the mandatory time to obtain a higher education entrance qualification from 13 to 12 years. It was implemented by most German federal states between 2001 and 2008, leading to double cohorts in several years (see, e.g., Büttner and Thomsen, 2015; Meyer et al., 2019).

variables used in terms of definitions and sources, Appendix Table A-2 provides summary statistics.

3.1 Housing Prices

To map the development of apartment rents, we use a special evaluation of the RWI-GEO-REDX on a quarterly basis on the district level, provided by the FDZ Ruhr at the RWI (Schaffner et al., 2022b).[9] This index offers several advantages over other data sources. First, it is a hedonic price index that accounts for quality changes. Second, it is based on price advertisements on Germany's leading digital real estate platform, ImmoScout24, covering a self-reported market share of about 60 percent (Breidenbach and Schaffner, 2020). Thus, it represents prices that are observable and well-known to a broad public looking for housing. Third, it only represents price offers for advertised rentals. While potentially biased upward, they are likely to influence the decision to move to a specific city more than actual rents. Fourth, it allows us to differentiate by different housing segments, which is useful for our study design. In our main analysis, we focus on apartment rents (as students are usually renters). Fifth, the RWI-GEO-REDX is usually only available on an annual basis. However, the FDZ provided us with a special evaluation on a quarterly basis, which gives us enough data points to make a valid estimate of structural breaks. Since this increases the noise in the data and leads to higher price volatility, we estimate structural breaks only for those districts where we have at least 50 observations in each quarter during our observation period.

However, using the RWI-GEO-REDX also has some disadvantages: Rooms in shared flats and in student residence halls are usually not listed on ImmoScout24, so they are not covered by the data. Moreover, our rental price index includes all types of apartments—not just those suitable for students (such as one-room apartments). However, it is reasonable to assume that prices develop proportionally and that increases in one segment of the market spill over into other segments. Indeed, in Appendix Figure A-4, we show that for a small subset of the top student cities, the yearly change in apartment rents from the RWI-GEO-REDX and in student-specific apartments from the IW Student Housing Price Index (Oberst and Voigtländer, 2018) over the period 2010 to 2019 are closely aligned and reasonably correlated ($\rho = 0.60$). Moreover, we can show that there is a seasonal pattern in the number of hits a rental advertisement receives that coincides with the start of the semester in October (winter term), when the vast majority of students enroll at college (see Appendix Figure A-5). This spike in August and September (as well as the subsequent dip in October) is much more pronounced in major university cities and for relatively cheap single apartments than on average.

[9] Klick and Schaffner (2021) provide a detailed description of the data set.

3.2 College Enrollments

We complement the housing price data with aggregated data on all enrollments at publicly acknowledged higher education institutions from the Federal Statistical Office of Germany (Destatis).[10] Using full record data from administrative student statistics has the advantage that they are less prone to measurement error and are available with a much higher temporal frequency and spatial coverage than survey data.[11] We can distinguish the data by detailed student characteristics, such as type of enrollment (first-time[12], second-level), type of degree, area of study and specific subject, gender, nationality (German vs. foreign), type of higher education institution, and district of high school graduation (however, not all information is crosswise available). Because we have information on the precise location of each institution and its individual campuses, we aggregate enrollment numbers at the district level and match them to the price data at the exact location where the students attend classes. We exclude correspondence colleges because studying there does not involve physical presence. Moreover, to avoid a potential bias due to campus closings or openings that could lead to sharp drops or booms in enrollment rates, we only consider those institutions that exist throughout our observation period from 2010 to 2019.

In total, we have 196 out of 401 districts with at least 100 first-year students in each observation year and are therefore considered college regions in our analysis (see Appendix Figure A-6). For six of them, we do not have sufficient data points to rely on the quarterly price index, so our estimation sample consists of 178 districts.

4 Empirical Strategy

To estimate the elasticity of college enrollment to changes in housing costs at the regional level, one could start with a straightforward model that exploits differences in growth in apartment rents across districts (see Appendix Figure A-7). This model builds on the intuition of the correlation patterns identified in Panel B of Figure 3, but eliminates all unobserved third factors that are constant over the observation period in a first-difference setting:

$$\Delta^{10-19} enrollments\ pc_r = \alpha_0 + \beta_{FD} \Delta^{10-19} \widehat{apartment\ rents}_r + \mathbf{X}_r \Gamma + u_r, \tag{1}$$

For our main outcome, we use the number of first-time enrollments per population aged 18-25 years, calculated as a 5-year rolling average. This approach mitigates the sensitivity

[10] The data are from an evaluation obtained from the ICE database of science and education departments in the state ministries (DZHW: ICEland dataset stock number 601, 80001, 80101, 80601, and 80801; data basis: special evaluation of the Federal Statistical Office of Germany).

[11] For example, the DZHW Panel Study of School Leavers with a Higher Education Entrance Qualification, a large representative survey on the transition of school leavers from school to higher education, is only available for three cohorts during our period of interest (2012, 2015, 2018).

[12] Unless otherwise stated, college enrollment or first-year students (as a synonym) always refers to first-time enrollment.

of our estimation to the definition of a particular year as a starting or end point, which may be subject to one-off effects and yearly fluctuations (see Section 2.3). It also allows us to compare average enrollment rates *before* the main boom period with those *during* the main boom period and follows closely the methodology used in prior research on this topic (Charles et al., 2018). $\Delta^{10-19} enrollments\ pc_r$ then denotes the change in per-capita enrollments in district r between 2010 and 2019. Since we use 5-year rolling averages, this represents the change between the average per-capita enrollment during 2015–2019 and the average per-capita enrollment during 2006–2010. Thus, β_{FD} denotes the effect of the total change in apartment rents during the peak phase of the boom period (2015-2019) to changes in enrollment rates during this period relative to the pre-boom period (2006-2010).[13] The first-difference approach controls for all unobserved district-specific factors that are constant over time, such as the general attractiveness or reputation of the colleges in the district. To further account for factors that cause differential trends in, say, the labor market or population, we add a vector of control variables, including i) population density, ii) the share of the population aged 18 to 25 years old, iii) the share of college-educated workers, and iv) the share of school leavers with a higher education entrance qualification at the 2010 level.

4.1 Two-Stage Least Squares (2SLS)

However, housing supply and demand are unlikely to be exogenous to other factors that influence college enrollment, such as amenity shocks or labor demand shocks. For example, if a particular city receives a positive shock to its attractiveness, this would attract both students and other demographic groups that drive housing prices. In addition, there may be a reverse causality bias, where students themselves raise housing prices as they move to a new city and search for housing (especially in so-called student cities where students comprise a significant share of the population). To address these endogeneity concerns, we adopt an identification strategy based on previous work by Charles et al. (2018) and Ferreira and Gyourko (2021), which involves detecting sharp changes in housing prices. This strategy is based on the premise that local housing market booms differ in magnitude and timing and that these sharp breaks are unrelated to local potential confounders, such as unobserved changes in labor supply or demand. Instead, Charles et al. (2018) can convincingly show for the US that the identified structural breaks in house prices cannot be explained by observable fundamental supply and demand factors but by speculative activity.

We adapt the strategy used by Charles et al. (2018) to the context of our study. First, we assume that rental prices follow a linear trend (instead of a log-linear trend), which is more in line with the development observed in Germany (see Figure 1). Second, we focus on apartment rents (rather than housing demand) because we are mainly interested in the direct costs of studying through higher housing costs (rather than opportunity

[13] We use different observation periods to show that the results are not sensitive to this kind of arbitrary choice. We also check whether the effects are sensitive to using 5-year averages, which is not the case.

costs). We argue that speculation-driven changes in purchase prices will, at some point, translate into changes in rents. This is motivated by standard economic theory in the vein of Poterba (1984), according to which the ratio of the annual rent of a house to its purchase price should be approximately equal to the user cost of capital, comprising real interest rates, property taxes, maintenance costs, and the expected annual rate of house price appreciation. Thus, in a rational, frictionless market, the price of a house should reflect the present discounted value of its future rental income. Now, if house prices are rising faster than rents (as observed in our case, see Figure 1, and in many other countries, see e.g. Hilber and Mense, 2021), this leads to a decline in the rental yield *ceteris paribus*, indicating that house prices are overvalued relative to fundamentals. For the market to return to equilibrium, we expect either a proportional adjustment in rents or, in the absence of excess demand, a downward correction in purchase prices. The theoretically established long-run relationship of house prices and rents is also supported empirically (Gallin, 2008) and experimentally (Hirota et al., 2020), although responses can be less than proportional due to market frictions and policy interventions.

To identify single structural breaks in the development of local apartment rents, we maximize the goodness of fit, measured as the log-likelihood, in the following district-specific regression, allowing the structural break to occur sometime between 2010:III and 2019:II:[14]

$$PI_r(t) = \omega_t + \tau_r t + \lambda_r (t - t_r^*) 1\{t > t_r^*\} + \zeta_{rt}, \tag{2}$$

where $PI_r(t)$ represents the price index in district r in year-quarter t. t_r^* is the date of the searched structural break that separates the district-specific time series into a linear time trend before the structural break ($\tau_r t$) and one afterward, where the size of the structural break (λ_r) is given by the difference-in-slopes (see for stylized examples of variations in structural breaks Appendix Figure B-1, and for a detailed overview of all estimated timings and magnitudes Appendix Table B-1). For about 80 percent of all districts in our sample, we find a significant structural break, with a range of varying magnitudes from small negative breaks to large positive breaks. As shown in Appendix Figure B-2, there is also substantial variation in the timing of the structural break, supporting our view of nonsynchronous local housing market booms. The modal quarter is 2016(Q1), with about ten percent of all districts having significant breaks. Most structural breaks (70%) occur in 2014, 2015, and 2016.

The size of the structural break (λ_r) is then used as an instrument for the 2010-2019 change in *apartment rents*$_r$ from equation (1) with the following first stage:

$$\Delta^{10-19} apartment\ rents_r = \alpha_0 + \gamma_{FS} \lambda_r + \epsilon_r, \tag{3}$$

[14] As is common practice, we trim the time series symmetrically at both ends of our observation window to account for a minimum segment length of two quarters.

In order to be a valid instrument for apartment rents, the structural break needs to be both relevant and exogenous to other factors influencing college enrollment. As illustrated in Panel A in Figure 4 and Appendix Table B-2, the (annualized) magnitude of the structural break is significantly and positively correlated with the total change in apartment rents between 2010 and 2019. This association holds for various specifications of the structural break, with all F-statistics exceeding ten. Unconditional rental price growth is 4.2% higher in the year after a positive structural break (see column 1 in Appendix Table B-3). Accounting for year fixed effects, the estimated jump after the structural break (relative year = 1) is still 3.9% (see column 2), so less than ten percent of the price growth can be explained by trends in rental prices that are common to all districts. In subsequent years, price growth rates decline again, but remain significantly higher than in the year before the structural break. In contrast, insignificant structural breaks are not related to a significant change in rental price growth before or after the structural break (see column 3), while negative breaks are associated with significantly lower growth rates thereafter (see column 4). This supports the validity of the structural break estimation and shows that there is a persistent trend shift in rental prices. Consistent with our argument above, purchase prices increased much more than rents before the structural break, leading to a significant increase in the price-to-rent ratio in the year of the structural break. In year two, the deviation returns to zero again, indicating that apartment rents caught up with the preceding increase in purchase prices (see Panel B in Figure 4).

< Insert Figure 4 here >

A key identifying assumption is that the structural break in apartment rents is mainly driven by speculative behavior in purchase prices and not by changes in fundamentals. We provide several pieces of evidence supporting this assumption. First, we examine whether the magnitude of the structural break is associated with certain regional pre-expansion characteristics (see Appendix Table B-4). Indeed, the size of structural breaks is larger in districts with a higher income and skill level and a lower housing supply level, which is to be expected to some extent. In contrast, many other regional characteristics prior to the housing market boom are not systematically correlated with the magnitude of the structural break. Second, we can show that the size of the structural break is considerably correlated with common indicators of price bubbles (Brausewetter et al., 2023). These include i) the initial price level, ii) the price-to-rent gap, iii) the price-to-income gap, and iv) residuals resulting from a simple regression of changes in apartment rents on changes in key supply and demand factors. Figure 5 shows that the larger these indicators of price bubbles are, the larger the structural break. Individually, each of these indicators explains 18 to 35 percent of the variation in the size of the structural break. By contrast, the explanatory power of key fundamentals, such as population density, the share of college-educated workers, or the living space per capita, is limited with respect to the structural break (R^2 between 0.00 and 0.14; see Appendix Figure B-3). Compared to the share of overall price growth that is actually explained by changes in these fundamentals (R^2 between 0.30 and 0.50; see also Brausewetter et al., 2023), this is quite small.

< Insert Figure 5 here >

One concern, however, may still be that the observed correlations between the structural break and changes in fundamental demand factors are indicative of shocks that affect both the size of the structural break and college enrollment rates, which would cast doubt on the exogeneity of the instrument. An indication of this concern would be if key supply and demand fundamentals of rental prices show simultaneous jumps around the timing of the structural break. To provide a check for this, we regress several regional characteristics on a series of dummies indicating the year relative to a positive and significant structural break. As shown in Appendix Figure B-4, we do not find any evidence for simultaneous discontinuities around a significant breakpoint. In addition, and reassuringly for our design, we can also rule out concerns about pretrends in the indicators considered, such as population, income, labor market factors, and sociodemographics. The same is true for variables measuring the financial and personnel endowments as well as amenity provision of higher education institutions, such as university funding, scientific personnel, seats in cafeterias, or places in student residence halls (see Appendix Figure B-5). None of these show significant deviations either before or after the boom, suggesting that there are no confounding shocks to amenities and endowments of higher education institutions that could have led to a systematic change in students' demand for these areas. Altogether, these results suggest that the structural break is, at most, only marginally driven by changes in fundamentals.

4.2 Difference-in-Differences (DiD) and Event Study Design

As a second estimation strategy, we exploit variation in both the timing and the magnitude of structural breaks in a difference-in-differences (DiD) setting. This approach allows us to control for time and district fixed effects and test whether changes in enrollment rates coincide with the timing of the breaks. Consistent with the previous design, we allow the structural breaks to occur between 2010:III and 2019:II, but extend our observation period to 2008 for a better identification of pretrends. The DiD model can be written as follows

$$enrollments\ pc_{rt} = \alpha_r + \delta_t + \beta_{DD}((Post\ t_r^*) \times \lambda_r) + \nu_{rt}, \tag{4}$$

where $enrollments\ pc_{rt}$ are first-time enrollments per population aged 18 to 25 years old in district r and year t. $(Post\ t_r^*)$ denotes all years after the timing of the district-specific structural break, and λ_r is the magnitude of the structural break. The district fixed effects, α_r, account for all time-fixed unobserved heterogeneity between districts, whereas the year fixed effects, δ_t, capture year-specific shocks that affect all districts equally.

Robust standard errors are clustered at the district level (ν_{rt}). The coefficient of interest is β_{DD}, which gives the effect of the size of the structural break on first-time enrollments per capita in years following the structural break. Compared to the IV estimates, the DiD estimates represent reduced-form estimates. By relaxing the exogeneity assumption, they identify the effect of sharp changes in apartment rents, irrespective of whether they are caused by speculative activity or other shocks (e.g., to labor demand). Moreover, the DiD specification can be easily translated into an event study design by replacing ($Post\ t_r^*$) with a set of indicators that reflect time relative to the year of the structural break. This approach allows us to visually assess whether the changes in enrollment rates occur around or after the structural break.

5 Results

5.1 Main Results

Table 1 presents our main results of the effect of a change in apartment rents from 2010 to 2019 on the change in 5-year average per-capita enrollment rates over the same period. Columns (1) and (2) show the OLS results, and columns (3) and (4) the 2SLS results, with the corresponding F-statistic at the bottom of the table (see also Appendix Table B-2 for the first stage results). In columns (2) and (4), we add a set of control variables measured at pre-boom levels in 2010, including population density, the share of the population aged 18 to 25 years old, the share of college-educated workers, and the share of school leavers with a higher education entrance qualification at the 2010 level. Panels B to C show the results for gender groups.

< Insert Table 1 here >

In all specifications, we find a negative effect of a change in apartment rents on changes in 5-year average per-capita enrollments. The 2SLS estimates are significant throughout and clearly larger than the OLS estimates. Reassuringly, although the standard errors increase in the control specification, this effect is relatively stable regardless of whether controls are included or not, supporting the exogeneity of our instrument. In our preferred IV specification, we estimate that a one percent increase in apartment rents from 2010 to 2019 reduces the 5-year average per-capita enrollment by -0.08 enrollments per 100 inhabitants aged 18-25. Thus, a one standard deviation increase in rental prices (+14%) leads to a decrease in the enrollment rate by 1.1 percentage points. In terms of gender differences, we find larger effects for men than for women, but the differences are small in the preferred specification. The effect in standard deviations is larger than the one obtained by Charles et al. (2018) for the US housing market boom. However, accounting for differences in the size of the boom and in the level of the enrollment rate, the effects are roughly comparable in percentage terms (but still larger). Explanations could be the indirect effect via opportunity costs and the larger return differential between different schools in the US setting, so this is in line with expectations. Assuming everything else is equal and scaling the effect by the average total rental price increase (+27%), we estimate in a simple back-of-the-envelope calculation that college enrollment rates in the average district are 16% lower in 2019 compared to the counterfactual of no price boom.

Table 2 presents the main DiD results of the change in enrollment rates after the structural break, scaled by its size, using the extended observation period from 2008 to 2019. Again, we add a set of now time-varying controls (column 2), including log population density, the share of the population aged 18 to 25 years old, the share of college-educated workers, and the share of school leavers with a higher education entrance qualification.

< Insert Table 2 here >

We consistently estimate a negative effect of the structural break on per-capita enrollment rates compared to the years before the structural break for the full sample. Without controls, we find that a one percent larger structural break decreases per-capita enrollment by –0.16. Compared to the 2SLS effect, this estimate represents the reduced-form in a panel setting. Scaling the 2SLS effect with the first stage relationship ($-0.08 \times 2.0 = -0.16$), both estimates are in line with each other. However, in contrast to the 2SLS results, the DiD results appear less robust to including time-varying controls for population and labor market factors. In the preferred specification in column (2), the effect is reduced to –0.096, but remains significant.

The interpretation of the reported effects in the DiD specification as causal, however, relies on the assumption of common trends. To examine the plausibility of this assumption, we run event study specifications, where the post-dummy from equation (4) is replaced by a set of indicators reflecting time relative to the structural break. This allows us to visually examine whether the change in enrollment rates occurs around or after the structural break. So far, the aggregate DiD estimates have suggested a negative deviation of per-capita enrollments in the period after the structural break relative to the period before. As is shown in Panel A in Figure 6, this does indeed coincide with the timing of the structural break. Two years after the structural break, there is a negative deviation in per-capita enrollments that persists over the subsequent years. Reassuringly, all coefficients prior to the structural break are insignificant, supporting the plausibility of the common trend assumption and removing concerns about a reverse causality mechanism, where a large influx of first-year students leads to a significant increase in apartment rents thereafter and ultimately to a decrease in enrollment.

< Insert Figure 6 here >

5.2 Heterogeneity and Intensive Margin

Having found an average negative effect of the apartment rent boom on college enrollment (extensive margin), we now examine whether certain subgroups are particularly affected and whether there are effects at the intensive margin. Heterogeneity between different groups of students is important both from an individual perspective due to heterogeneity in returns and from a policy perspective. Focusing first on the type of higher education institution (see Table 3), we find strong evidence that the average effects are driven by first-time enrollment rates at universities. The coefficients for first-year students at universities are highly significant and negative, while all other types of institutions, including UAS, show much smaller effects closer to zero. Consistent with this finding are the effects for heterogeneity by area of study (see Appendix Table C-1) and by degree type (see Appendix Table C-2). We estimate significant negative effects of apartment rents particularly for those students studying areas and degrees that are predominantly offered at universities, such as teaching degrees and state examinations as well as natural sciences.

< Insert Table 3 here >

Moreover, we examine whether a change in apartment rents affects not only the decision to study at a particular location but also how long to study there (intensive margin). Table 4 presents the results for using the average study duration as the outcome variable. Overall, we find no evidence that the housing market boom reduced the length of study for the first degree, as the effects are very small and insignificant. For the average total study length of consecutive programs, there are even positive effects but comparatively small and also not statistically significant. The positive effect would be consistent with students having to work more during their studies and extend their studies to cover the increased cost of living. Although we do not find evidence of an effect on the share of the young population that is marginally employed (so-called mini-jobs) (see Appendix Table C-3), the response could also be in terms of working hours, for which we do not have data. Moreover, we look at multiple enrollments (as opposed to first-time, as in our main results) and obtain some evidence of negative effects in the DiD specification (see Appendix Table C-4). This holds particularly for first-year students who switch subjects or institutions, suggesting also some response beyond the initial cost-benefit considerations of whether and where to go to college.

< Insert Table 4 here >

5.3 Mechanisms

Location Effect

In the following, we investigate mechanisms for the identified average negative effect on college enrollment and its particular appearance at universities. Several explanations are conceivable for the latter: First, it might be a pure location effect. Universities are usually located in large cities, while UAS are more widely spread across urban and rural areas. However, when we split our sample of districts into three tiers according to population density and size (i: rural, ii: urbanized, and iii: large cities; see Appendix Table C-5), we find negative effects for all types of districts but particularly large ones for rural and urbanized districts. Hence, the effects are larger outside of large cities with more than 100,000 inhabitants. The first two groups include, for example, small university cities such as Bamberg, Bayreuth, Ludwigsburg, or Weimar, as well as small UAS cities such as Esslingen, Fulda, or Schwerin. These college locations in second- and third-tier areas offer a similar housing supply and even more student amenities (in terms of student housing and cafeteria seats per student), but are significantly smaller, less tertiarized, and offer far fewer consumption amenities than large cities.[15] Consistently, when we examine heterogeneity by type of institution only within large cities, we find sizeable negative effects for students at universities but not for those at UAS. Thus, the location effect is unlikely to serve as the sole explanation.

Mobility

Therefore, we investigate a second explanation for this finding: differences in mobility patterns. As shown in Section 2.1, university students are much more mobile than students at UAS, and these highly mobile students could be particularly affected by changes in apartment rents, as they cannot compensate for higher rents by staying with their parents or exploiting local networks and knowledge about the housing market. Therefore, we distinguish first-year students who obtained their higher education entrance qualification in Germany by the region of that qualification and divide them into i) out-of-state students, ii) out-of-labor market region (LMR) but within-state students, and iii) within-LMR students (see Table 5). Indeed, we find sizeable negative effects of changes in apartment rents only for mobile students moving into the college region from outside the state boundaries. This effect is not driven by college regions directly located on the federal-state border, as we find very similar effects for first-year students who move more than 200 kilometers to the college location (excluding international students; see Appendix Table C-6). In contrast, the effects for out-of-LMR but within-state as well as within-LMR students are close to zero and insignificant.

< Insert Table 5 here >

Moreover, the negative effects for out-of-state movers are similarly large for both universities and UAS, but these students play a relatively small role for UAS in general. This suggests that it is indeed differences in mobility behavior that drive the effect, rather than unobserved institutional or student heterogeneity. Taken together, the results indicate that the rental price boom reduced interregional student mobility so that students were less likely to cross state borders or more over long distances. As Appendix Table C-7 further shows, this pattern is observed in both West Germany and in East Germany, although the estimates in East Germany are less precise due to the smaller sample size.

Purchase Prices

As a next step, we examine the transmitting mechanisms of the impact of local housing

[15] We measure consumption amenities using the number of geotagged photos posted on social media in the early 2010s by Ahlfeldt et al. (2023).

price booms on college enrollment. As we discussed in the beginning, they may have an effect through direct costs, opportunity costs, or income and credit constraints in terms of family resources. Therefore, we look at apartment and house *purchase* prices rather than rental prices and re-estimate our empirical models accordingly. Comparing the effects for the different housing price indicators, we find that they are indeed strongest for apartment rents and not present for apartment or house purchase prices (see columns 3 and 4 in Table 6). This aligns with our expectations for the German context and supports the interpretation of rising direct costs of studying as the primary mechanism during the German housing market boom—compared to, for example, the US, where opportunity costs play a larger role. We also find very similar effects when we use a price index that gives the deviation of rental prices from the national average (rather than from a base period) (see column 2). Thus, students appear to be sensitive to both absolute and relative increases in rental prices. At the same time, this also supports the validity of the main structural break estimation, since these breaks should be large enough to represent both absolute and relative price increases.

< Insert Table 6 here >

Outside Options

Our results thus far show that an increase in apartment rents reduces college enrollment within an average district. This raises the question of what alternatives students pursue instead: They could either study elsewhere (e.g., at a cheaper location) or pursue alternatives such as direct labor market entry or vocational education and training (VET). However, since the effects are driven by mobile students, the location of the rent increase is not the same as the location of residence, complicating the matter of pinpointing any effects on outside options. Nevertheless, we explore these potential channels and first consider employment outcomes. Table 7 presents estimates from our OLS, 2SLS, and DiD designs while using the youth employment rate (individuals under the age of 25 years), the share of youth employment in construction, the share of youth employment in the FIRE sector, and the number of VET applicants with a higher education entrance qualification per capita as outcome variables.

< Insert Table 7 here >

As shown in Table 7, the estimates for the youth employment rate are significantly positive, while the effects on the share of employment in the construction and the FIRE sectors are consistently negative. This suggests that the housing market boom coincided with growth in overall employment. However, this growth tended to occur outside of construction and the FIRE sector, leaving opportunity costs in construction and related services relatively unaffected but increasing opportunity costs in the overall labor market. As a result, some students may find it more attractive to enter the labor market directly after high school graduation. However, this group is quite small, representing only four percent of a graduating cohort permanently and an additional five percent temporarily as a transitional activity (Schneider et al., 2017). For the quantitatively larger group of those high school graduates with a higher education entrance qualification who apply for a VET (about 20% in 2015; Schneider et al. 2017), however, we report effects close to zero, indicating no response at this margin.

5.4 Robustness Checks

Identification of Structural Breaks

We perform several checks to examine the robustness of our results. First, we check how sensitive the results are to the estimation of structural breaks. In our baseline estimation, we allowed only for one structural break per district during our observation window due to econometric problems associated with the sequential or simultaneous identification of multiple structural breaks and structural break inference (Bai, 1999; Bai and Perron, 1998). However, a local housing market may experience multiple housing market booms or busts (Ferreira and Gyourko, 2021). Therefore, we sequentially test for the number of breakpoints and then re-estimate the segmented relationship with the number of breakpoints chosen. For about 80% of districts in our estimation, we cannot reject the null hypothesis of two breakpoints, which supports the choice of our baseline estimation. However, for a robustness check, we allow for two breaks and use alternative measures of the instrument, such as the maximum break size identified (column 2), the sum of all break sizes (column 3), or the first breakpoint identified (column 4) (see Appendix Table C-8). Although there are some changes in effect sizes in both directions, the estimates resulting from multiple breaks are consistently negative. In addition, our results are robust to excluding structural breaks with negative values (2) and setting insignificant breaks to zero (3) (see Appendix Table C-9). Moreover, we find that the results hold when we estimate structural breaks on a yearly basis (see column 4).

Permutation Tests

Second, we perform randomization tests where we permute the magnitude and the year of the structural break in rental prices in each college region (see Appendix Figure C-1).[16] This exercise suggests that it is very unlikely to obtain estimates as large as ours, once the magnitude of rental price booms is randomly allocated in the 2SLS setting (see Panel A). In contrast, this is not the case for the timing of the break in the DiD setting (see Panel B). However, the randomization generates relatively many extreme results due to the limited amount of conceivable timings (10).

Model and Outcome Specifications

Third, one may be concerned that our results are biased through the definition of our outcome (as 5-year per-capita averages), the spatial aggregation level, and the selected

[16] We allow the structural breaks to occur in each year of our observation period and their magnitude to vary within a normal distribution around the mean and standard deviation that we observe in our data.

observation window (2010-2019). Therefore, we provide additional evidence where we use population weights (2) and raw per-capita enrollment as the outcome variable (3) (see Appendix Table C-10). Since these checks do not lead to concerning differences in results, we are confident that our effects are not selectively driven by the definition of our outcome variable as 5-year averages of enrollments per population aged 18 to 25 years. The population-weighted coefficients, however, suggest that the population effects are slightly smaller than the effects reported in the main analysis, which refer to the average district. In addition, we estimate the effects at the level of labor market regions (see Appendix Table C-11). By doing so, we can show that the results are clearly not driven by a too narrow definition of a college region, as the effects remain robust at a higher aggregation level. Furthermore, we try different time periods, such as 2009-2019, 2011-2019, 2012-2019, and 2013-2019, for the estimation of structural breaks and the observation period in the OLS and IV results. Again, we consistently find negative effects, suggesting that our results are not too sensitive to the choice of the observation window (see Appendix Table C-12).

Placebo Tests: Non-affected Periods and Fields of Study

Fourth, we run placebo tests to see if changes in apartment rents during the main boom period (2010-2019) predict changes in enrollment rates prior to the period of interest (2006-2010). If our main estimates from Table 1 were not causal but driven by pre-existing trends in enrollment rates, we should find significant results here. However, since the coefficients are small and insignificant, this strongly supports our causal interpretation of the results (see Appendix Table C-13). Moreover, we estimate the effects for a group of students who should not be affected (or at least much less affected) by an increase in apartment rents. As described in Section 2.3, medicine, pharmacy, and dentistry have centralized admissions, and students are allocated to study places all over Germany. Therefore, they should be less sensitive to housing prices, as they can either accept or decline the offered study place. Appendix Table C-14 presents the results for these fields of study, all of which are very close to zero, supporting our interpretation of the results.

Confounding Policies and Shifts in the Higher Education System and the Housing Market

Fifth, one might be concerned that our effects on college enrollment are driven by confounding reforms and changes in the higher education system. For instance, the share of international students has grown over time, and they may be affected differently by changes in apartment rents. Therefore, we look separately at students who received their higher education entrance qualification in Germany and those who did not (see Appendix Table C-15). On the one hand, international students could be less prone to rental price increases due to limited choice of location and a higher accommodation rate in subsidized student residence halls (Apolinarski and Brandt, 2018). On the other hand, they cannot compensate by staying with their parents, have lower financial income than domestic students (Middendorff et al., 2017; Apolinarski and Brandt, 2018), and experience discrimination in the housing market (Flage, 2018). Indeed, we find negative effects of similar magnitude for both groups, suggesting that international students are also affected in their location choice and supporting the relevance of the latter mechanism. This is also backed up by descriptive evidence from the DZHW Social Survey, according to which three-fifths of international students in Germany reported major difficulties in finding suitable housing in 2016, compared to 47% in 2012 (Apolinarski and Brandt, 2018).

Next, we check for a potential confounding effect of different trends in student housing supply and of parallel educational reforms (G8 reform and introduction and abolition of tuition fees) (see Appendix Table C-16), with little effect on the estimation results. In addition, we check the robustness and generalizability of our results to the inclusion of newly established institutions of higher education (see column 2 in Appendix Table C-17). This leads to a small to noticeable reduction in the negative effect, suggesting that there is indeed some founding effect from the establishment of new colleges (branches) that can counteract rent increases. Finally, we exclude all so-called cooperative state universities that integrate academic studies with paid on-the-job training (dual studies) (see column 3 in Appendix Table C-17). This increases the coefficients, indicating a small dampening effect of institutions that offer dual studies where students earn some money.

6 Conclusion

Existing evidence on the effects of housing market booms on college enrollment has focused on opportunity costs and liquidity constraints as the main mechanisms. In this paper, we examine how rental prices directly affect college enrollment at the regional level. We focus on the context of Germany, where there are basically no tuition fees and housing costs account for the largest share of students' budgets. For causal identification, we exploit district-specific variation in the magnitude and timing of structural breaks in the evolution of apartment rents over the period 2010 to 2019. We can show that these unanticipated jumps in rental prices lead to a significant and persistent trend shift; moreover, they are less likely to result from changes in local demand and supply fundamentals, but rather from speculative activity in purchase prices.

We find that increases in rental prices significantly reduced college enrollment in the average district. We estimate that a one standard deviation increase in rental prices (+14%) leads to a decrease in the enrollment rate by 1.1 percentage points. This effect is linked to a reduction in interregional student mobility: the negative effects result primarily from mobile students moving across state borders and over long distances (>200km) to the college location. Due to their larger catchment areas, universities are especially affected. In terms of heterogeneity by location, we report negative effects mainly in smaller regions outside the very large cities. We interpret these findings as a higher price sensitivity of students in locations that offer lower consumption amenities. In contrast to the findings of Lovenheim (2011), Lovenheim and Reynolds (2013), and Charles et al. (2018) for the US housing market, we do not find any evidence of a *purchase* price effect translated through increased labor market opportunities in construction or through family wealth. Therefore, we view our findings as more consistent with expectations of the tuition-free context of Germany, where direct housing costs are the more relevant mechanism than opportunity costs or family wealth.

Our results help to explain the recent slowdown in the higher education expansion in Germany—at least to some extent and in some areas. They are also policy relevant, as attracting and retaining high-skilled workers remains an important goal for many regions, and universities play a vital role in doing so. In this context, our analysis points toward affordable housing as a location factor that is indeed valued by students and influences their higher education enrollment and migration decisions. The provision of affordable housing (be it private, subsidized, or public) can therefore be seen as a key tool for policymakers to increase the attractiveness of a region for young and well-educated individuals. This is particularly important for peripheral regions, which may lose their comparative advantage of low living costs due to disproportionate increases in housing prices. At the same time, it can help to reduce regional inequalities in housing prices and skilled labor.

References

Ahlfeldt, G. M., Heblich, S., and Seidel, T. (2023). Micro-geographic property price and rent indices. *Regional Science and Urban Economics*, 98:103836.

Altonji, J. G., Blom, E., and Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics*, 4(1):185–223.

Apolinarski, B., Becker, K., Borchert, L., Bornkessel, P., Brandt, T., Fabian, G., Heienberg, S., Isserstedt, W., Kandulla, M., Leszczensky, M., Link, J., Middendorff, E., Netz, N., Poskowsky, J., Schnitzer, K., Weber, S., Wolter, A., Schreiber, J., Schröder, M., Müig-Trapp, P., Kahle, I., and Narten, R. (2023). Pooled Data Set 10th - 21st Social Survey 1982 - 2016. Data Collection: 1982-2016. Version: 3.0.0. Data Package Access Way: SUF: Download. `https://doi.org/10.21249/DZHW:ssypool:3.0.0`.

Apolinarski, B. and Brandt, T. (2018). Ausländische Studierende in Deutschland 2016. Ergebnisse der Befragung bildungsausländischer Studierender im Rahmen der 21. Sozialerhebung des Deutschen Studentenwerks durchgeführt vom Deutschen Zentrum für Hochschul- und Wissenschaftsforschung. Technical report, Federal Ministry of Education and Research, Berlin.

Bai, J. (1999). Likelihood ratio tests for multiple structural changes. *Journal of Econometrics*, 91(2):299–323.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1):47–78.

Bauer, T. K., Rulff, C., and Tamminga, M. (2019). Berlin calling - Internal migration in Germany. Ruhr Economic Papers 823, RWI – Leibniz Institute for Economic Research (RWI), Essen.

Berlingieri, F., Gathmann, C., and Quinckhardt, M. (2022). College openings and local economic development. CEPR Discussion Paper DP17374, Centre for Economic Policy Research, London.

Bernstein, A. and Struyven, D. (2022). Housing lock: Dutch evidence on the impact of negative home equity on household mobility. *American Economic Journal: Economic Policy*, 14(3):1–32.

Brausewetter, L., Thomsen, S. L., and Trunzer, J. (2023). Regional supply and demand fundamentals in the german housing price boom. *German Economic Review*, online first.

Breidenbach, P. and Schaffner, S. (2020). Real estate data for Germany (RWI-GEO-RED). *German Economic Review*, 21(3):401–416.

Brown, J. and Matsa, D. A. (2020). Locked in by leverage: Job search during the housing crisis. *Journal of Financial Economics*, 136(3):623–648.

Büttner, B. and Thomsen, S. L. (2015). Are we spending too many years in school? Causal evidence of the impact of shortening secondary school duration. *German Economic Review*, 16(1):65–86.

Carneiro, P., Liu, K., and Salvanes, K. G. (2023). The supply of skill and endogenous technical change: Evidence from a college expansion reform. *Journal of the European Economic Association*, 21(1):48–92.

Charles, K. K., Hurst, E., and Notowidigdo, M. J. (2018). Housing booms and busts, labor market opportunities, and college attendance. *American Economic Review*, 108(10):2947–2994.

Chetty, R., Friedman, J. N., Saez, E., Turner, N., and Yagan, D. (2020). Income segregation and intergenerational mobility across colleges in the United States. *The Quarterly Journal of Economics*, 135(3):1567–1633.

Deming, D. J., Yuchtman, N., Abulafi, A., Goldin, C., and Katz, L. F. (2016). The value of postsecondary credentials in the labor market: An experimental study. *American Economic Review*, 106(3):778–806.

Deutsche Bundesbank (2022). Indikatorensystem zum Wohnimmobilienmarkt. Preisindikatoren. https://www.bundesbank.de/de/statistiken/indikatorensaetze/indikatorensystem-wohnimmobilienmarkt/indikatorensystem-zum-wohnimmobilienmarkt-775496 (last accessed: December 12, 2023).

Deutscher Bundestag (2023). Stellungnahme des Deutschen Studierendenwerks (DSW) zum Expertengespräch des Ausschusses für Bildung, Forschung und Technikfolgenabschätzung des Deutschen Bundestags zum Thema Programm Junges Wohnen und zu sozialer Infrastruktur für Studierende und Auszubildende. Ausschussdrucksache 20(18)106b, Deutscher Bundestag, Auschuss für Bildung, Forschung und Technikfolgenabschätzung.

Deutsches Studierendenwerk (2020). Student service organisations facts and figures: Issues 2009/2010 - 2019/2020. Technical report, Deutsches Studierendenwerk, Berlin.

Dynarski, S., Page, L., and Scott-Clayton, J. (2022). College costs, financial aid, and student decisions. NBER Working Paper 30275, National Bureau of Economic Research, Cambridge, MA.

Federal Ministry of Education and Research (BMBF) (2023). Tabelle 2.5.75. Übergang zur Hochschule - Entwicklung grundlegender Kennzahlen. https://www.datenportal.bmbf.de/portal/de/Tabelle-2.5.75.html (last accessed: December 12, 2023).

Federal Statistical Office (Destatis) (2022). Monetäre hochschulstatistische Kennzahlen: Fachserie 11 Reihe 4.3.2. 2020. Technical report, Federal Statistical Office.

Federal Statistical Office (Destatis) (2023a). Database of the Federal Statistical Office of Germany. https://www-genesis.destatis.de/genesis/online (last accessed: July 11, 2023).

Federal Statistical Office (Destatis) (2023b). Regional Database Germany. https://www.regionalstatistik.de/ (last accessed: July 11, 2023).

Ferreira, F. and Gyourko, J. (2021). Anatomy of the beginning of the housing boom across U.S. metropolitan areas. *Review of Economics and Statistics*, pages 1–16.

Ferreira, F., Gyourko, J., and Tracy, J. (2010). Housing busts and household mobility. *Journal of Urban Economics*, 68(1):34–45.

Flage, A. (2018). Ethnic and gender discrimination in the rental housing market: Evidence from a meta-analysis of correspondence tests, 2006–2017. *Journal of Housing Economics*, 41:251–273.

Foote, A. (2016). The effects of negative house price changes on migration: Evidence across U.S. housing downturns. *Regional Science and Urban Economics*, 60:292–299.

Gallin, J. (2008). The long-run relationship between house prices and rents. *Real Estate Economics*, 36(4):635–658.

GeoBasis-DE/BKG (2018). Verwaltungsgebiete 1:250 000 (Ebenen), Stand 01.01.2018 (VG250 01.01.). https://gdz.bkg.bund.de/index.php/default/digitale-geodaten/verwaltungsgebiete/verwaltungsgebiete-1-250-000-ebenen-stand-31-12-vg250-ebenen-31-12.html.

Goetz, C. F. (2013). Falling house prices and labor mobility: Evidence from matched employer-employee data. US Census Bureau Center for Economic Studies Paper No. CES-WP- 13-43.

Gunderson, M. and Oreopolous, P. (2020). Chapter 3 - Returns to education in developed countries. In Bradley, S. and Green, C., editors, *The Economics of Education (Second Edition)*, pages 39–51. Academic Press.

Hemsley-Brown, J. and Oplatka, I. (2015). University choice: what do we know, what don't we know and what do we still need to find out? *International Journal of Educational Management*, 29(3):254–274.

Hilber, C. A. L. and Mense, A. (2021). Why have house prices risen so much more than rents in superstar cities? Geography and Environment Discussion Paper 30, Department of Geography and Environment, London School of Economics, London.

Hirota, S., Suzuki-Löffelholz, K., and Udagawa, D. (2020). Does owners' purchase price affect rent offered? Experimental evidence. *Journal of Behavioral and Experimental Finance*, 25:100260.

Hochschulrektorenkonferenz (HRK) (2021). Statistische Daten zu Studienangeboten an Hochschulen in Deutschland Studiengänge, Studierende, Absolventinnen und Absolventen: Wintersemester 2021/2022. Statistiken zur Hochschulpolitik 1/2021, Berlin.

Hoekstra, M. (2009). The effect of attending the flagship state university on earnings: A discontinuity-based approach. *Review of Economics and Statistics*, 91(4):717–724.

HUD's Office of Policy Development and Research (PD&R) (2015). Barriers to success: Housing insecurity for U.S. college students. Insights into housing and community development policy, PD&R.

Kirkeboen, L. J., Leuven, E., and Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3):1057–1111.

Klick, L. and Schaffner, S. (2021). Regional real estate price indices for Germany, 2008 – 2019: RWI–GEO–REDX. *Jahrbücher für Nationalökonomie und Statistik*, 241(1):119–129.

Knoll, K., Schularick, M., and Steger, T. (2017). No price like home: Global house prices, 1870–2012. *American Economic Review*, 107(2):331–353.

Kroher, M., Beuße, M., Isleib, S., Becker, K., Ehrhardt, M.-C., Gerdes, F., Koopmann, J., Schommer, T., Schwabe, U., Steinkühler, J., Völk, D., Peter, F., and Buchholz, S. (2023). Die Studierendenbefragung in Deutschland: 22. Sozialerhebung. Die wirtschaftliche und soziale Lage der Studierenden in Deutschland 2021. Technical report, Federal Ministry of Education and Research, Berlin.

Kroher, M., Leuze, K., Thomsen, S. L., and Trunzer, J. (2021). Did the "Bologna Process" achieve its goals? 20 years of empirical evidence on student enrolment, study success and labour market outcomes. IZA Discussion Papers 14757, Institute of Labor Economics, Bonn.

Lang, S. and Schwabe, U. (2023). Graduates' early wages in Germany: Does a university's status of excellence make the difference? *Research in Social Stratification and Mobility*, 83:100765.

Le Monde (2022). France's chronic student housing shortage blocks access to education for less well-off. `https://www.lemonde.fr/en/education/article/2022/06/10/france-faces-chronic-student-housing-shortage-that-blocks-access-to-education-for-less-well-off_5986270_104.html` (last accessed: July 11, 2023).

Lovenheim, M. and Smith, J. (2022). Returns to different postsecondary investments: Institution type, academic programs, and credentials. NBER Working Paper 29933.

Lovenheim, M. F. (2011). The effect of liquid housing wealth on college enrollment. *Journal of Labor Economics*, 29(4):741–771.

Lovenheim, M. F. and Reynolds, C. L. (2013). The effect of housing wealth on college choice: Evidence from the housing boom. *Journal of Human Resources*, 48(1):1–35.

Meyer, T., Thomsen, S. L., and Schneider, H. (2019). New evidence on the effects of the shortened school duration in the german states: An evaluation of post–secondary education decisions. *German Economic Review*, 20(4):e201–e253.

Middendorff, E., Apolinarski, B., Becker, K., Bornkessel, P., Brandt, T., Heißenberg, S., and Poskowsky, J. (2017). Die wirtschaftliche und soziale Lage der Studierenden in Deutschland 2016. Zusammenfassung zur 21. Sozialerhebung des Deutschen Studentenwerks – durchgeführt vom Deutschen Zentrum für Hochschul- und Wissenschaftsforschung. Technical report, Federal Ministry of Education and Research, Berlin.

MLP SE (2022). MLP Studentenwohnreport 2022: In Kooperation mit dem Institut der deutschen Wirtschaft. Technical report, MLP SE, Wiesloch.

Oberst, C. and Voigtländer, M. (2018). IW-Studentenwohnpreisindex 2018: Mietpreisunterschiede zwischen Hochschulstandorten weiten sich. IW-Report 36/2018, German Economic Institute (IW), Cologne.

Poterba, J. M. (1984). Tax subsidies to owner-occupied housing: An asset-market approach. *Quarterly Journal of Economics*, 99(4):729.

RWI and ImmobilienScout24 (2023). RWI real estate data - Apartments for rent: RWI-GEO-RED. Version: 1. RWI – Leibniz Institute for Economic Research. http://doi.org/10.7807/immo:red:wm:v8.

Sá, C., Florax, R. J., and Rietveld, P. (2012). Living arrangement and university choice of dutch prospective students. *Regional Studies*, 46(5):651–667.

Schaffner, S., Thiel, P., RWI, and ImmobilienScout24 (2022a). RWI-GEO-REDX: Regional real estate price index for Germany, 2008-06/2022. Version: 1. RWI – Leibniz Institute for Economic Research. Dataset. http://doi.org/10.7807/immo:redx:v9.

Schaffner, S., Thiel, P., RWI, and ImmobilienScout24 (2022b). RWI-GEO-REDX: Regional real estate price index for Germany, 2008-12/2022. Version: 1. RWI – Leibniz Institute for Economic Research. Dataset. Special evaluation of quarterly values on district-level. http://doi.org/10.7807/immo:redx:v10.

Schneider, H., Franke, B., Woisch, A., and Spangenberg, H. (2017). Erwerb der Hochschulreife und nachschulische Übergänge von Studienberechtigten: Studienberechtigte 2015 ein halbes Jahr vor und ein halbes Jahr nach Schulabschluss. Forum Hochschule 4/2017, DZHW, Hanover.

Statistics of the Federal Employment Agency (BA Statistics) (2023a). Gemeldete Bewerberinnen und Bewerber für Berufsausbildungsstellen insgesamt und mit dem Schulabschluss Fachhochschulreife und Allgemeine Hochschulreife.

Statistics of the Federal Employment Agency (BA Statistics) (2023b). Sozialversicherungspflichtig Beschäftigte unter 25 Jahre nach der Klassifikation der Wirtschaftszweige 2008 (Auswahl).

StepStone (2020). StepStone Gehaltsreport für Absolventen 2020/2021. Technical report, Düsseldorf.

Südwestrundfunk (SWR) (2022). WG-Zimmer dringend gesucht. Tausende Studierende zu Semesterbeginn in BW noch ohne Unterkunft. https://www.swr.de/swraktuell/baden-wuerttemberg/studierende-wohnungsnot-100.html (last accessed: July 11, 2023).

The Guardian (2022). Uk student housing reaching 'crisis point' as bad as 1970s, charity warns. https://www.theguardian.com/education/2022/dec/26/uk-student-housing-reaching-crisis-point-as-bad-as-1970s-charity-warns (last accessed: July 11, 2023).

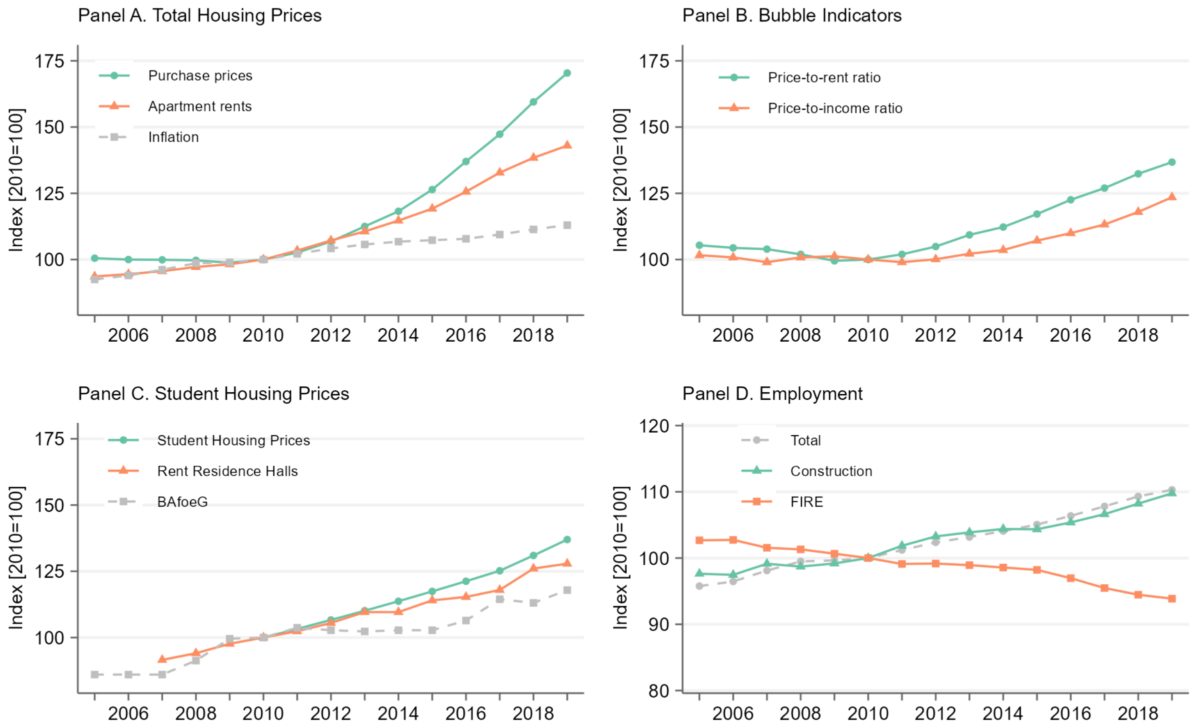
The Washington Post (2022). Rising rents add to college students' scramble for affordable housing. https://www.washingtonpost.com/education/2022/08/09/college-student-housing-costs/ (last accessed: July 11, 2023).

Wetzstein, S. (2017). The global urban housing affordability crisis. *Urban Studies*, 54(14):3159–3177.

Winters, J. V. (2020). In-state college enrollment and later life location decisions. *Journal of Human Resources*, 55(4):1400–1426.

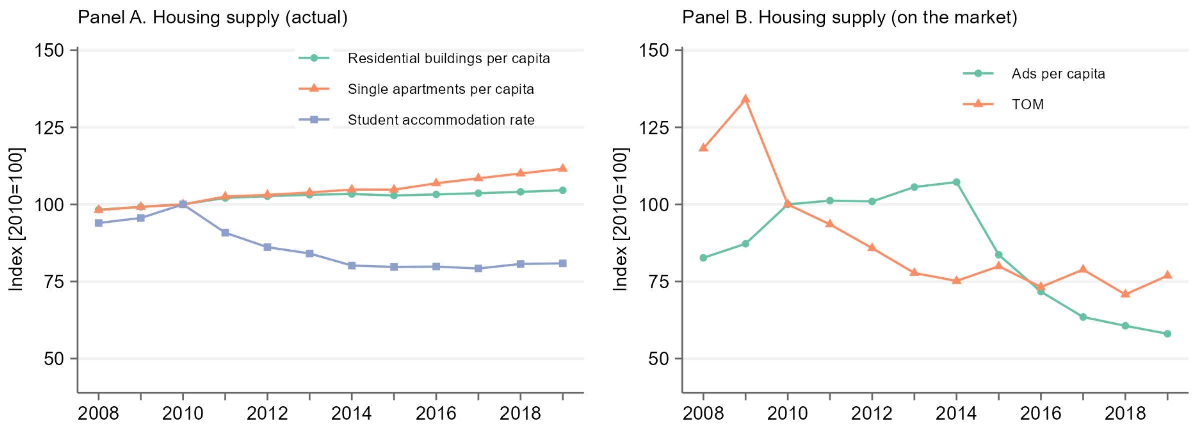
Figures and Tables

Figure 1: Housing Market Indicators, Germany, 2005-2019



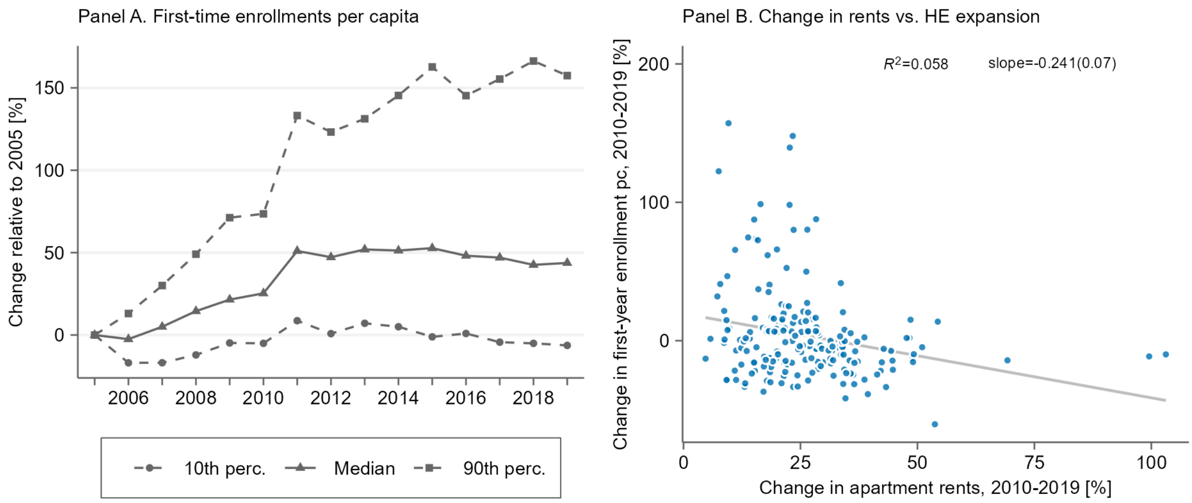
Notes: The figure shows the evolution of aggregate housing market indicators in Germany from 2005 to 2019. Panel A shows apartment purchase prices and apartment rents in colors and the inflation rate in gray. Panel B presents the price-to-rent ratio and the price-to-income ratio. Panel C shows student housing prices and average rents for student residence halls in colors and the average monthly BAfoeG support per student in gray. Panel D depicts total employment, employment in construction and employment in finance, insurance, and real estate (FIRE) services. Data sources for Panels A-B are the Deutsche Bundesbank's residential property price indices based on price data from bulwiengesa AG (Deutsche Bundesbank, 2022), for Panel C the IW Student Housing Price Index (Oberst and Voigtländer, 2018; MLP SE, 2022) for student housing prices, Deutsches Studierendenwerk (2020) for rents in student residence halls, and Destatis (2023a) for BAfoeG support, and for Panel D Destatis (2023a).

Figure 2: Average Housing Supply per District, Germany, 2008-2019



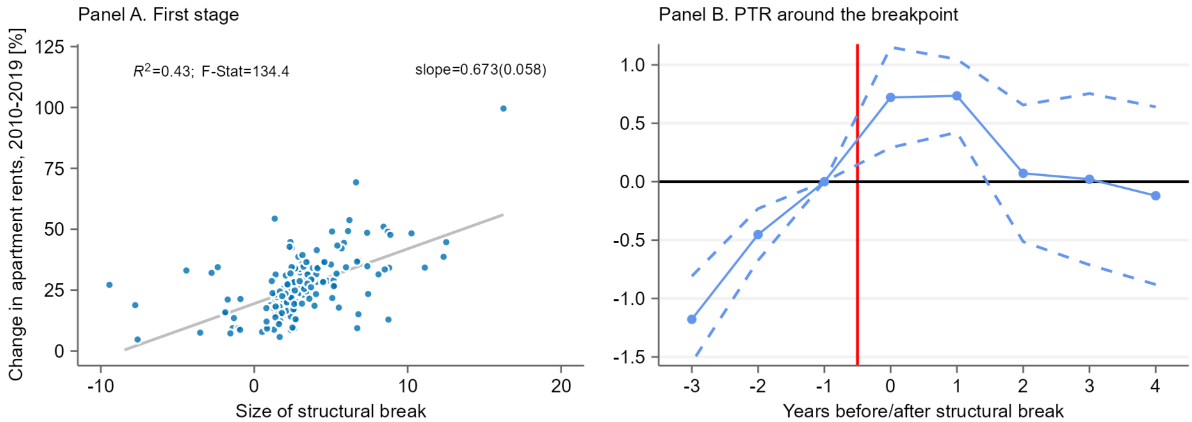
Notes: The figure shows the evolution of mean housing market indicators per district in Germany from 2008 to 2019. Panel A shows the indicators of actual supply, measured as the number or residential buildings per capita, the number of single apartments per capita, and the number of places in residence halls per student (accommodation rate). Panel B presents indicators of supply available on the market, measured as the number of advertisements per capita for apartments listed for rent and the average number of days an advertisement for rental apartments is listed (time-on-the-market (TOM)). Luxury apartments are excluded and only ads published in the last month when they then exit the listing website are included. Data source for Panel A is Destatis (2023b) and Deutsches Studierendenwerk (2020), data source for Panel B is the RWI-GEO-REDX (Schaffner et al., 2022a) for ads per capita and the RWI-GEO-RED (RWI and ImmobilienScout24, 2023) for TOM.

Figure 3: Regional Variation in Enrollment Trends



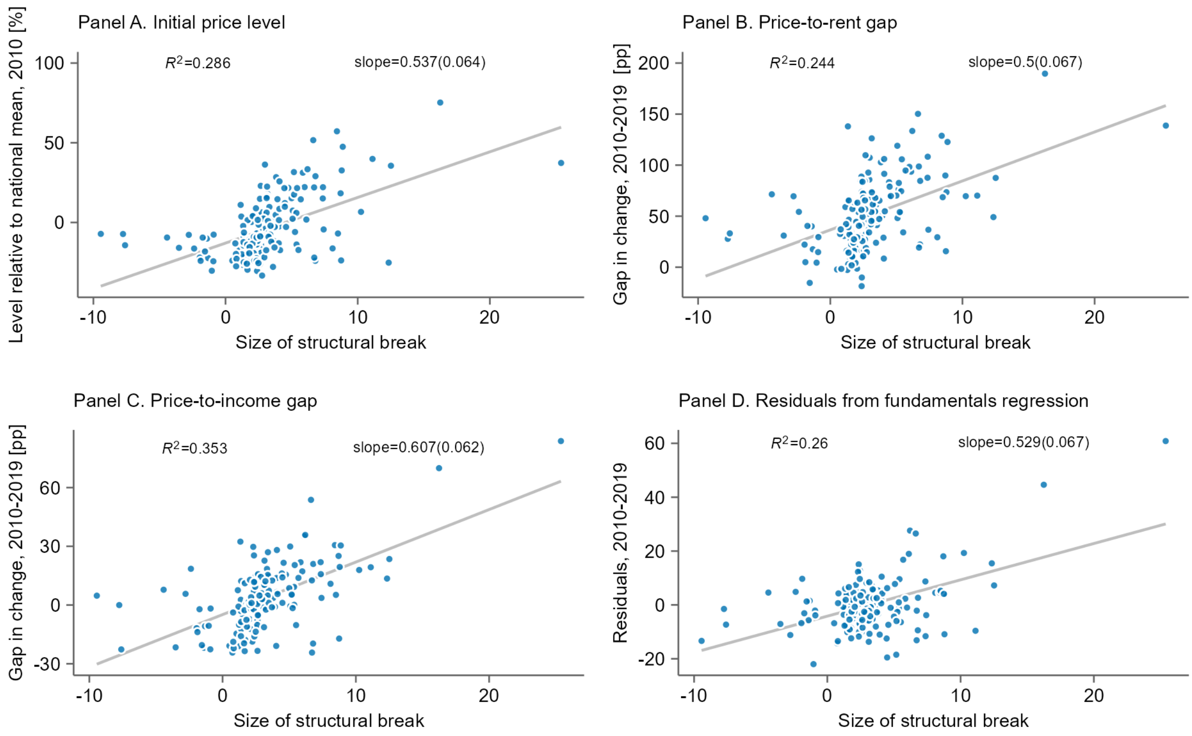
Notes: The figure shows the evolution of college enrollment rates across German districts. Panel A ranks all districts by their change in the college enrollment rate from 2010 to 2019 and plots the median, the top, and the bottom deciles of college enrollment change. Panel B shows the correlation between the change in apartment rents from 2010 to 2019 (x-axis) and the change in first-time enrollments per capita over the same period (y-axis). The gray solid line represents a trend line resulting from a linear fit, with the corresponding R-squared and slope noted at the top. College enrollment refers to the sample and definition used in our main analysis (see Section 3.2). Data on college enrollment are from the ICE database of the science and education departments in the state ministries (DZHW: ICEland dataset stock number 80101; data basis: special evaluation of the Federal Statistical Office of Germany). Data on apartment rents are from the RWI-GEO-REDX (Schaffner et al., 2022a).

Figure 4: Instrument Relevance



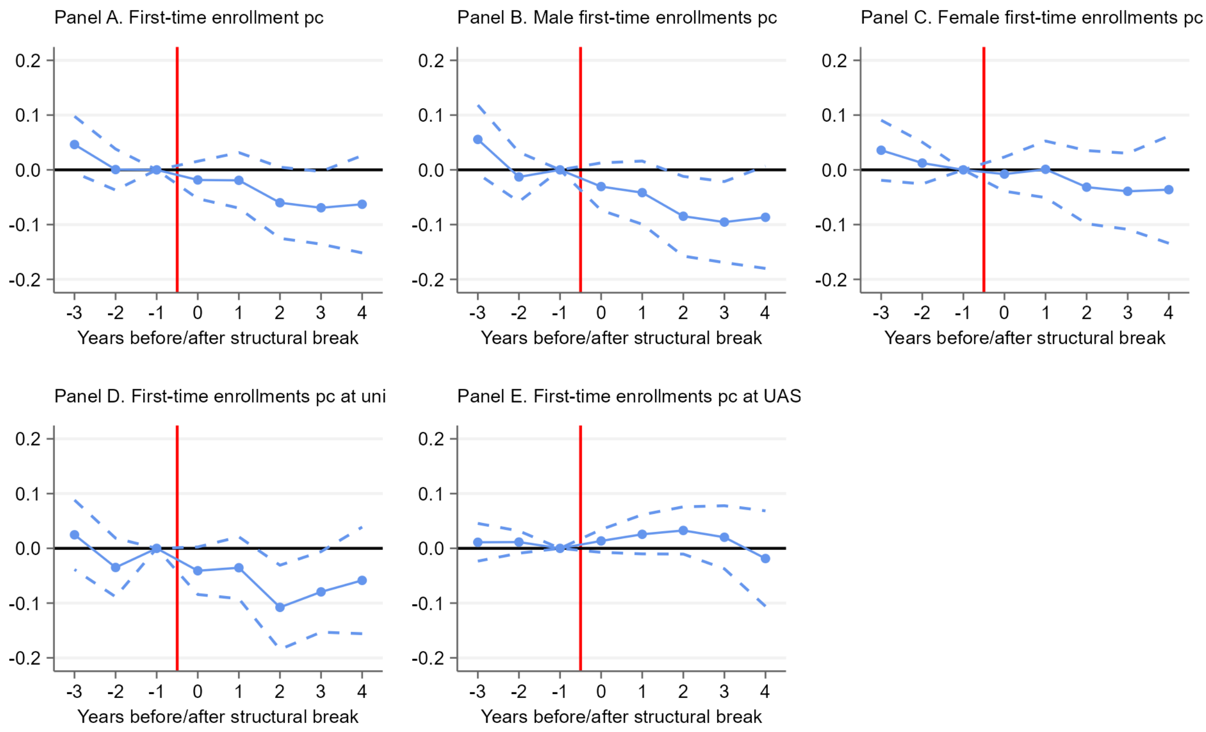
Notes: The figure presents evidence to support the relevance and exogeneity of the instrument. Panel A shows the correlation between the size of the structural break (x-axis) and the change in apartment rents from 2010 to 2019 (y-axis). The gray solid line represents a trend line resulting from a linear fit, with the corresponding R-squared and slope noted at the top. Panel B shows event study estimates of the effect of the size of the structural break on the price-to-rent ratio. The regression includes indicator variables for each year before and after the year of the estimated structural break, scaled by its magnitude. The last lag and lead are binned to capture all events before and after, respectively. The sample period in each district is restricted to five years before and six years after the estimated structural break (if available). All estimations include region and year fixed effects. Robust standard errors are clustered at the district level. 95% confidence intervals are shown.

Figure 5: Housing Boom Indicators and Size of Structural Break



Notes: The figure shows the correlation between several indicators of a housing boom (y-axis) and the size of the structural break (x-axis). Panel A uses the initial level of apartment rents in 2010 (relative to the national average), Panel B uses the price-to-rent gap, i.e., the difference between the change in apartment purchase prices and apartment rents between 2010 and 2019, Panel C uses the price-to-income gap, i.e., the difference between the change in apartment rents and household income per capita between 2010 and 2019, and Panel D uses the residuals from a simple regression explaining total price growth from 2010 to 2019 by changes in a set of fundamentals over the same period. These fundamentals include the population density, household income per capita, the share of college-educated workers, living space per capita, and the share of small apartments. The gray solid line represents a trend line resulting from a linear fit, with the corresponding R-squared and slope noted at the top.

Figure 6: Event Study Estimates of First-Time Enrollment Effects



Notes: The figure shows event study estimates of the apartment rent boom on first-time college enrollment per capita. The regressions include indicator variables for each year before and after the year of the estimated structural break, scaled by its magnitude. All specifications include year and district fixed effects as well as baseline controls (see text for details). We use an effect window of -3 to 4, as this corresponds to our relatively short observation period but all leads and lags are still available for at least about two-thirds of the districts. The last lag and lead are binned to capture all events before and after, respectively. Robust standard errors are clustered at the district level. 95% confidence intervals are shown.

Table 1: Main Estimates of the Effect of Rental Price Changes on First-Time College Enrollment

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Panel A. Total Sample.				
Δ Apartment rents, 2010-2019	-0.013	-0.020	-0.057**	-0.081***
	(0.014)	(0.017)	(0.022)	(0.029)
Observations	178	178	178	178
Mean level 10	9.107	9.107	9.107	9.107
Panel B. Men.				
Δ Apartment rents, 2010-2019	-0.024	-0.022	-0.072***	-0.092***
	(0.015)	(0.019)	(0.024)	(0.032)
Observations	178	178	178	178
Mean level 10	9.249	9.249	9.249	9.249
Panel C. Women.				
Δ Apartment rents, 2010-2019	-0.002	-0.018	-0.042*	-0.071**
	(0.015)	(0.018)	(0.023)	(0.030)
Observations	178	178	178	178
Mean level 10	8.871	8.871	8.871	8.871
First stage F-statistic	-	-	134.4	48.8
Controls		x		x

Notes: The table presents the main OLS and 2SLS estimates of the effect of a change in apartment rents on the change in annual first-time enrollments per capita. Both the dependent and the independent variables are measured as the long-difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. The F-statistic from the corresponding first stage is shown at the bottom of the table. Panels A to C show the results for different demographic groups. Controls include log population density, the share of college-educated workers, the share of young population, and the share of school leavers with a higher education entrance qualification in 2010. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010. Standard errors are shown in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Difference-in-Differences Estimates of the Effect of Rental Price Changes on First-Time College Enrollment

	First-time enrollment pc	
	(1)	(2)
Panel A. Total Sample.		
Post × magnitude structural break	-0.158***	-0.096***
	(0.050)	(0.035)
Observations	2136	2136
Mean level	10.997	10.997
Panel B. Men.		
Post × magnitude structural break	-0.211***	-0.118***
	(0.062)	(0.038)
Observations	2136	2136
Mean level	10.975	10.975
Panel C. Women.		
Post × magnitude structural break	-0.103**	-0.070*
	(0.045)	(0.039)
Observations	2136	2136
Mean level	10.908	10.908
District FE	x	x
Year FE	x	x
Controls		x

Notes: The table shows the main DiD estimates of the effect of the size of the structural break in apartment rents on first-time enrollment per capita relative to the period before the break. Panels A to C show the results for different demographic groups. Controls include log population density, the share of college-educated workers, the share of young population, and the share of school leavers with a higher education entrance qualification. "Mean level" refers to the mean of the outcome variable over our observation period. Robust standard errors are clustered at the district-level and shown in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effects on College Enrollment: Heterogeneity by Type of Higher Education Institution

	Uni (1)	UAS (2)	Art (3)	Admin (4)	Priv (5)
Panel A. OLS estimates.					
Δ Apartment rents, 2010-2019	-0.026	-0.014	-0.002	-0.013	-0.012
	(0.022)	(0.014)	(0.002)	(0.011)	(0.012)
Observations	89	150	36	41	68
Mean level 10	10.896	3.903	0.395	0.830	0.707
Panel B. 2SLS estimates.					
Δ Apartment rents, 2010-2019	-0.117***	-0.016	-0.004	0.003	-0.040**
	(0.038)	(0.025)	(0.002)	(0.018)	(0.019)
Observations	89	150	36	41	68
Mean level 10	10.896	3.903	0.395	0.830	0.707
Panel C. DiD estimates.					
Post × magnitude struct. break	-0.090**	-0.005	-0.001	-0.000	0.000
	(0.040)	(0.031)	(0.002)	(0.024)	(0.036)
Observations	1068	1800	432	492	816
Mean level	12.112	5.241	0.431	1.139	1.183

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by type of higher education institution. "Uni" includes universities, colleges of education and theology; "UAS" refers to universities of applied sciences; "Art" includes colleges of art and music; "Public Admin" refers to colleges of public administration; and "Priv" includes only privately funded institutions of higher education. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Effects on Average Study Time [in Semester]

	Total (1)	First Study (2)	Consec. Study (3)
Panel A. OLS estimates.			
Δ Apartment rents, 2010-2019	0.001	0.003	0.026*
	(0.006)	(0.006)	(0.014)
Observations	168	168	154
Mean level 10	9.717	9.493	12.250
Panel B. 2SLS estimates.			
Δ Apartment rents, 2010-2019	-0.002	-0.003	0.034
	(0.010)	(0.010)	(0.023)
Observations	168	168	154
Mean level 10	9.717	9.493	12.250
Panel C. DiD estimates.			
Post × magnitude struct. break	0.004	0.002	0.028
	(0.012)	(0.013)	(0.023)
Observations	2069	2064	1936
Mean level	9.766	9.215	12.393

Notes: The table shows estimates of the effect of apartment rents on average study duration per graduate (in semester). Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. The average study duration is further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Effects on Mobility of First-Year Students: Heterogeneity by Type of Higher Education Institution

	Out of state			Within state, out of LMR			Within district		
	Total	Uni	UAS	Total	Uni	UAS	Total	Uni	UAS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. OLS.									
Δ^{10-19} Rents	-0.019**	-0.015	-0.015**	0.003	-0.001	0.000	0.014***	0.005	0.006*
	(0.008)	(0.010)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)	(0.004)	(0.003)
Observations	178	89	150	178	178	178	178	178	178
Mean level 10	2.614	3.359	0.973	2.745	1.513	1.083	2.483	1.347	1.056
Panel B. 2SLS.									
Δ^{10-19} Rents	-0.041***	-0.031*	-0.032**	-0.005	-0.013*	0.003	0.006	-0.006	0.008
	(0.013)	(0.016)	(0.013)	(0.011)	(0.007)	(0.008)	(0.008)	(0.006)	(0.005)
Observations	178	89	150	178	178	178	178	178	178
Mean level 10	2.614	3.359	0.973	2.745	1.513	1.083	2.483	1.347	1.056
Panel C. DiD.									
Post $\times$ break size	-0.023	-0.003	-0.022	0.003	-0.005	0.011	0.007	-0.008	0.019**
	(0.018)	(0.015)	(0.023)	(0.012)	(0.009)	(0.007)	(0.012)	(0.008)	(0.007)
Observations	2136	1068	1800	2136	2136	2136	2136	2136	2136
Mean level	3.045	3.522	1.332	3.136	1.544	1.368	2.936	1.496	1.333

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by region of high school graduation. "Out of state" refers to those first-year students who graduated from high school outside of the federal state where the higher education institution is located, "Within state, out of LMR" refers to those who graduated within the same state but outside the labor market region (LMR) of the institution, and "Within district" refers to those who graduated within the same district as the higher education institution. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effects on First-Time College Enrollment: Different Housing Price Indicators

	Main (1)	ApRent Idx (2)	ApPurc (3)	HouPurc (4)
Panel A. OLS estimates.				
Δ Housing Prices, 2010-2019	-0.020	-0.085***	-0.013	-0.009
	(0.017)	(0.031)	(0.009)	(0.008)
Observations	178	178	176	178
Mean level 10	10.185	10.185	10.185	10.185
Panel B. 2SLS estimates.				
Δ Housing Prices, 2010-2019	-0.081***	-0.102**	-0.030	0.003
	(0.029)	(0.044)	(0.044)	(0.018)
Observations	178	151	140	154
Mean level 10	10.185	10.185	10.185	10.185
Panel C. DiD estimates.				
Post × magnitude struct. break	-0.096***	-0.063	-0.004	-0.000
	(0.035)	(0.047)	(0.032)	(0.000)
Observations	2136	1812	1680	1848
Mean level	10.997	10.997	10.997	10.997

Notes: The table shows estimates of the effect of different housing price indicators on first-time enrollment per capita. Column (1) presents the main results presented in Table 1 and 2, column (2) uses the deviation of rental prices from the national average, column (3) uses changes in apartment purchase prices, and column (4) uses changes in house purchase prices. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in the respective price indicator. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. Due to data limitations, for columns (2) to (4) only yearly price series are used for the structural break estimation, explaining the differenes in observations. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effects on Youth Employment and VET Applications

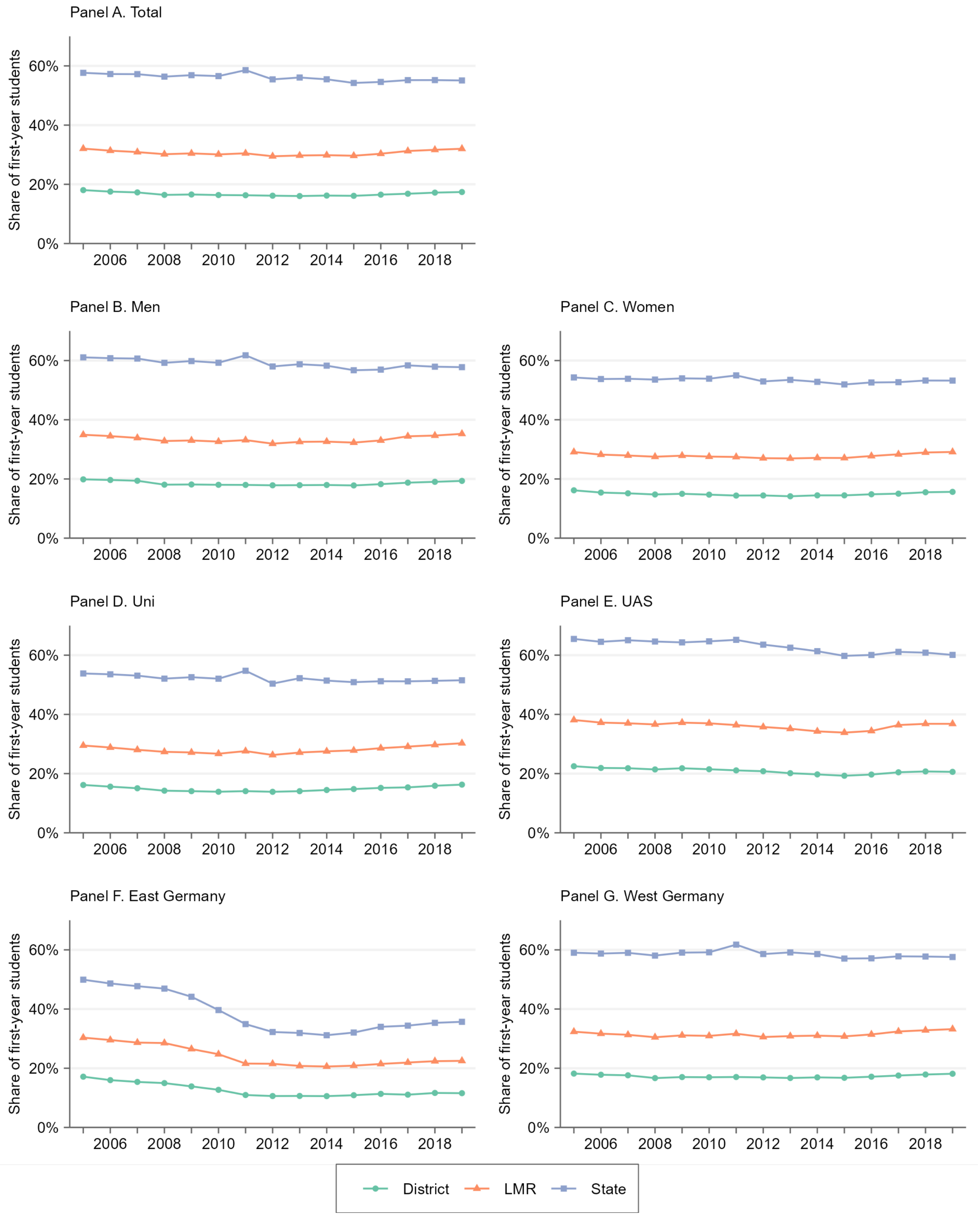
	Emp. rate	Share emp. constr.	Share emp. FIRE	VET hq
	(1)	(2)	(3)	(4)
Panel A. OLS estimates.				
Δ Apartment rents, 2012-2019	0.116***	-0.005	-0.014***	-0.001
	(0.017)	(0.005)	(0.003)	(0.003)
Observations	178	178	178	178
Mean level 10	38.356	7.058	3.195	2.109
Panel B. 2SLS estimates.				
Δ Apartment rents, 2012-2019	0.121***	-0.014*	-0.020***	-0.000
	(0.025)	(0.008)	(0.004)	(0.004)
Observations	178	178	178	178
Mean level 10	38.356	7.058	3.195	2.109
Panel C. DiD estimates.				
Post × magnitude struct. break	0.235***	-0.016	-0.035***	0.011
	(0.057)	(0.012)	(0.009)	(0.007)
Observations	2136	2136	2136	2136
Mean level	36.627	6.951	3.052	2.051

Notes: The table reports estimates of the effect of apartment rents on various employment outcomes for the age group under 25 years. Column (1) uses the employment rate of workers under 25 years, column (2) the share of youth employment in the construction sector, column (3) the share of youth employment in the FIRE sector, and column (4) the number of vocational education and training (VET) applications with a higher education entrance qualification (hq) per population aged 18 to 25 years. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2012 and 2019. Due to data limitations of the employment variables, we can only use this shortened observation period. The employment outcomes are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Tables and Figures

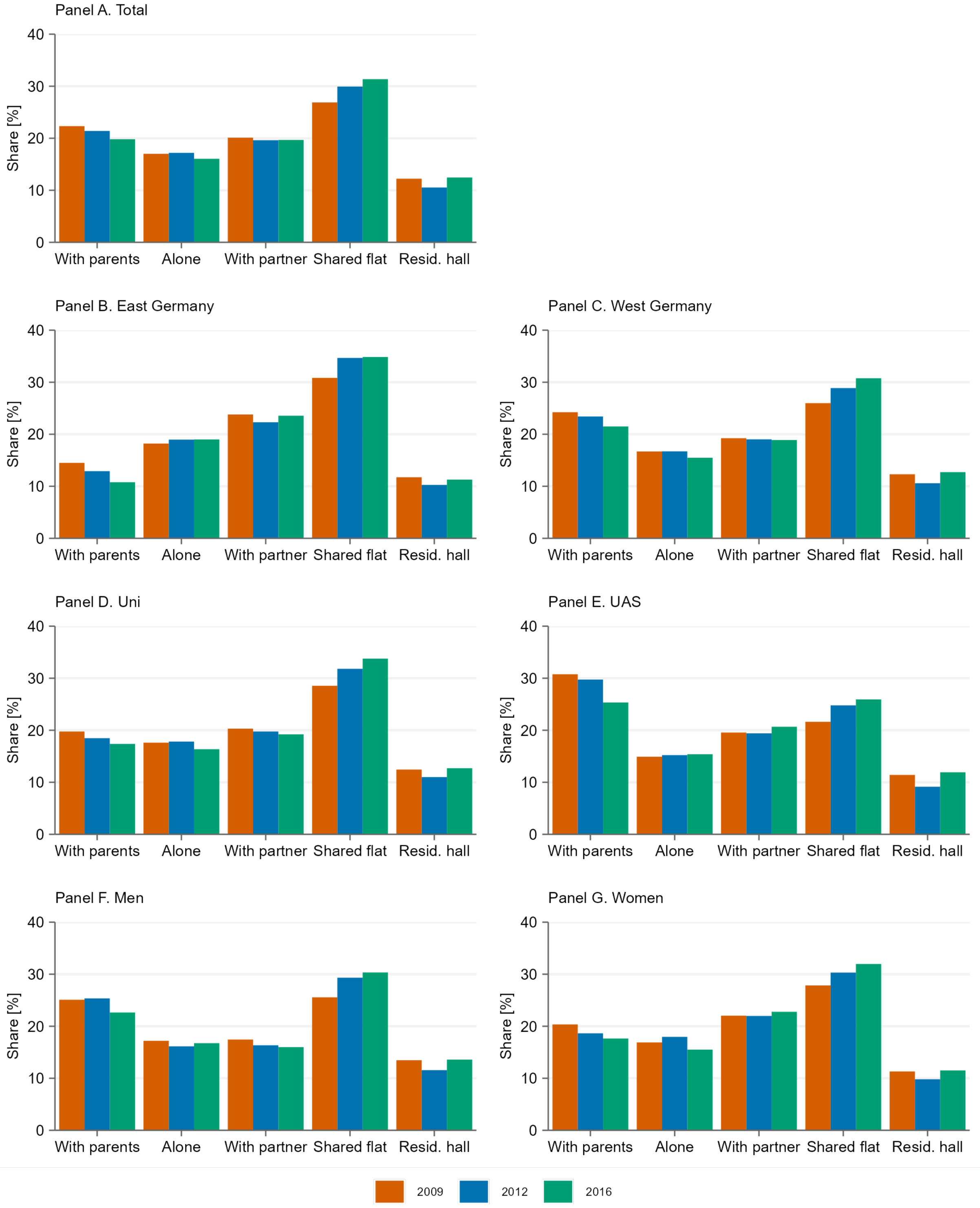
A Additional Descriptives

Figure A-1: Student Migration



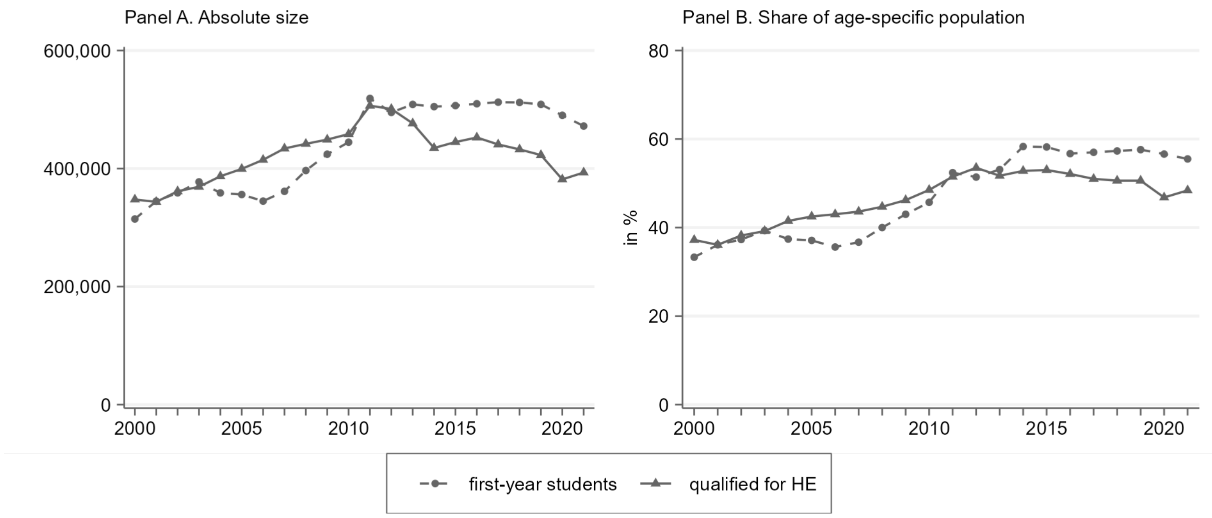
Notes: The figure shows the overall share of students who obtained their higher education entrance qualification in the same federal state, labor market region (LMR), and district as the institution of higher education. Panel A refers to the full sample of institutions included in our analysis, while Panels B-G differentiate by gender, type of higher education institution, and by region. Both domestic and international students included. The data source is the ICE database of science and education departments in the state ministries (DZHW: ICEland dataset stock number 80801; data basis: special evaluation of the Federal Statistical Office of Germany).

Figure A-2: Housing Situation



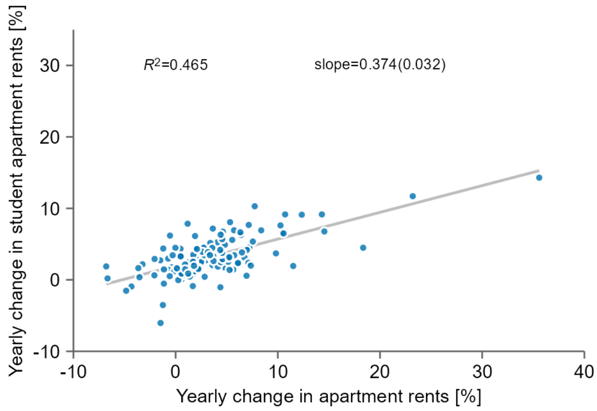
Notes: The figure shows the proportions of students living with their parents, alone, with a partner in a private apartment, in a shared flat or in a student residence hall. Panel A refers to the total sample of students, while Panels B-G differentiate by region, type of higher education institution, and gender. No sample restrictions. The data source are the 2009, 2012, and 2016 cohorts of the Pooled Data Set 10^{th} to 21^{st} Social Survey 1982-2016 (Apolinarski et al., 2023).

Figure A-3: Transition to Higher Education over Time



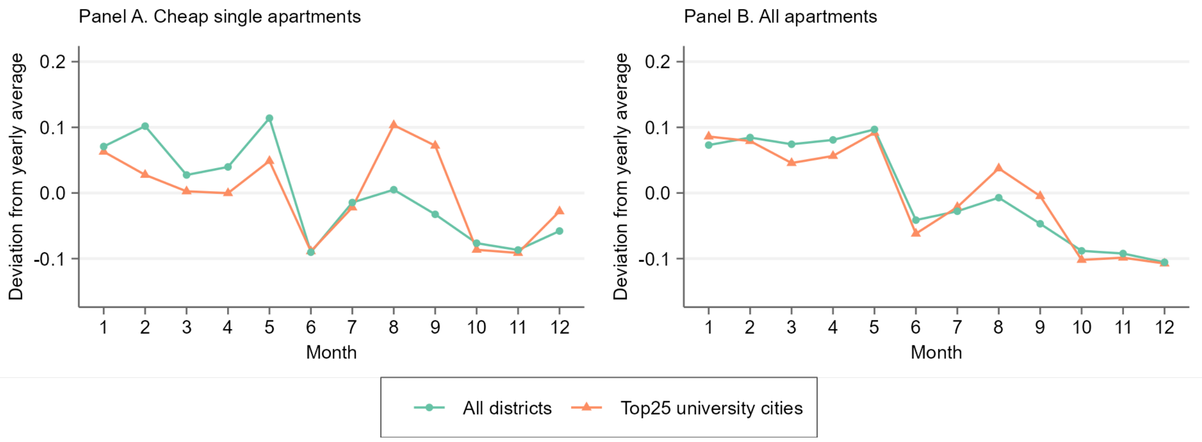
Notes: The figure shows the evolution of persons qualified to enter higher education and first-year students. Panel A refers to the absolute size, while Panel B refers to the share of school leavers qualified to enter higher education and the share of students in their first semester (first-time enrollment), respectively, in the age-specific population. Data source is the Federal Statistical Office of Germany (BMBF, 2023).

Figure A-4: Correlation between Annual Growth in Total Apartment Rents and Student Apartment Rents



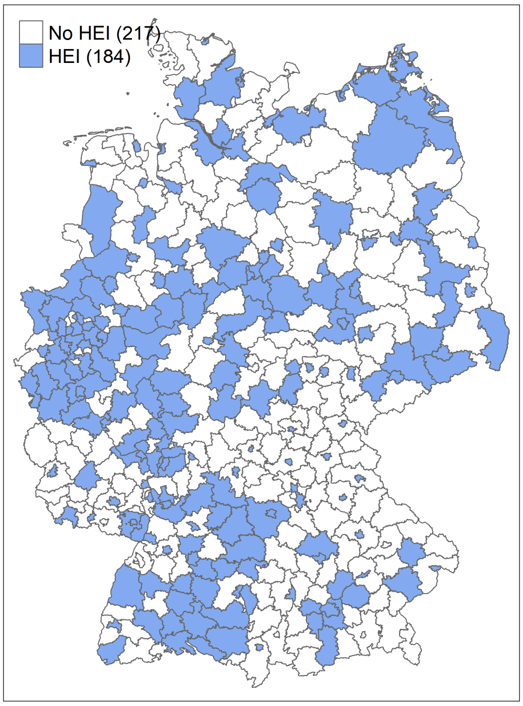
Notes: The figure shows the correlation between the annual growth of total apartment rents (x-axis) and in student apartment rents (y-axis) for a small sample of student cities (N=17) for the years 2010 to 2019: Aachen, Berlin, Bochum, Bonn, Frankfurt, Göttingen, Greifswald, Hamburg, Heidelberg, Jena, Karlsruhe, Kiel, Cologne, Leipzig, Magdeburg, Munich, and Münster. The data for total apartment rents are from the RWI-GEO-REDX (Schaffner et al., 2022a), the data for student apartment rents are from the IW Student Housing Price Index (Oberst and Voigtländer, 2018; MLP SE, 2022).

Figure A-5: Average Hits per Ad by Month of Year



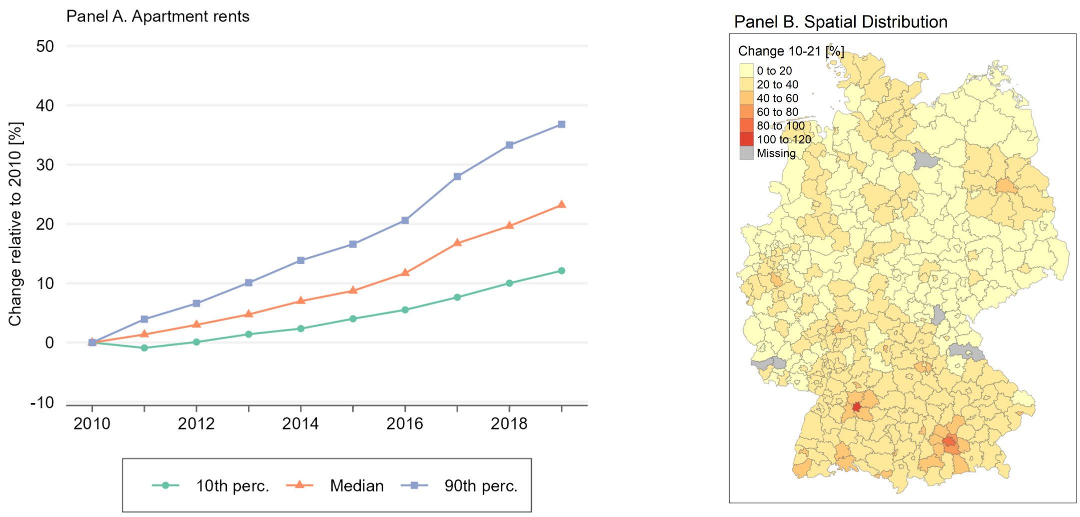
Notes: The figure shows the average number of hits an apartment listed for rent received on ImmoScout24 by month of the year, given as the deviation from the overall annual average. Panel A uses only single apartments with a rental price below 600 euros, and Panel B uses all apartments. Top25 university cities refer to the 25 districts that have the largest number of students per population in 2010. Luxury apartments are excluded and only ads published in the last month when they then exit the listing website are included. The data on hits per ad are from the RWI-GEO-RED (RWI and ImmobilienScout24, 2023).

Figure A-6: Districts with Higher Education Institutions



Notes: The figure shows the spatial distribution of districts with higher education institutions (HEIs) in Germany for selected years. A HEI region is defined as a district with more than 100 first-year students (first enrollment) in every of our observation years (2010-2019). Administrative districts are defined according to the state of territory in 2019. Data on college enrollments are from Destatis; geodata are from GeoBasis-DE/BKG (2018).

Figure A-7: (Spatial) Distribution of Apartment Rent Growth (2010-2019) across Districts



Notes: The figure shows the change in apartment rents compared to the base year 2010 by district quantiles (Panel A) and their spatial distribution (Panel B). The data on apartment rents are from the RWI-GEO-REDX (Schaffner et al., 2022a); the geodata are from GeoBasis-DE/BKG (2018).

Table A-1: Definition and Sources of Variables Used

Variable	Description	Unit	Source
Apartment rents	Change in the regional price index for apartment rents at the district level relative to 2008	Index [2008=100]	RWI-GEO-REDX (Schaffner et al., 2022a)
Apartment purchase prices	Change in the regional price index for apartment purchase prices at the district level relative to 2008	Index [2008=100]	RWI-GEO-REDX (Schaffner et al., 2022a)
House purchase prices	Change in the regional price index for house purchase prices at the district level relative to 2008	Index [2008=100]	RWI-GEO-REDX (Schaffner et al., 2022a)
Population density	Number of inhabitants per territorial area (as of 2008)	Ratio	Destatis (2023b)
Share of females	Share of female persons per total population at the place of residence	%	Destatis (2023b)
Share of migrants	Share of migrants per total population at the place of residence	%	Destatis (2023b)
Unemployment rate	Share of unemployed persons per total labor force	%	Destatis (2023b)
Household income per capita	Average household income per capita	In 1,000€ pc	Destatis (2023b)
Share of college-educated workers	Share of employees subject to social security contributions with academic qualification at place of work	%	Destatis (2023b)
Employment rate	Share of persons in employment per total labor force	%	Destatis (2023b)
Female labor force participation	Share of female employees per total employees subject to social security contributions at place of work	%	Destatis (2023b)
Employment in construction	Share of persons in employment in construction as a percentage of total persons in employment	%	Destatis (2023b)
Employment in FIRE	Share of persons in employment in finance, insurance and real estate (FIRE) services as a percentage of total persons in employment	%	Destatis (2023b)
Youth employment rate	Share of persons in employment aged 20-25 as a percentage of total population aged 18-25	%	Destatis (2023b)
Youth employment in construction	Share of persons under age 25 employed in construction as a percentage of total persons in employment under age 25	%	BA Statistics (2023b) upon request
Youth employment in FIRE	Share of persons under age 25 employed in finance, insurance and real estate (FIRE) services as a percentage of total persons in employment under age 25	%	BA Statistics (2023b) upon request
VET applicants per capita	Applicants for vocational education and training (VET) with a higher education entrance qualification per population aged 18-25	Ratio	BA Statistics (2023a) upon request
Living space per capita	Living area in residential buildings per capita	In m^2	Destatis (2023b)
Share of small apartments	Share of apartments with 1 and 2 rooms per total apartments in residential and non-residential buildings	%	Destatis (2023b)
Share of big apartments	Share of apartments with 5 or more rooms per total apartments in residential and non-residential buildings	%	Destatis (2023b)
Completed apartments per capita	Completed apartments in residential buildings with 3 or more apartments per 1,000 inhabitants	Ratio	Destatis (2023b)
Building permits per capita	Building permits for new apartments in residential buildings per 1,000 inhabitants	Ratio	Destatis (2023b)

Continued on next page.

Table A-1: Definition and Sources of Variables Used (cont.)

Variable	Description	Unit	Source
Accommodation rate	Number of units in student residence halls (operated by the Studierendenwerk) per 100 students	Ratio	Deutsches Studierendenwerk (2020)
Cafeteria seats per student	Number of seated places in dining halls and cafeterias (operated by the Studierendenwerk) per 100 students	Ratio	Deutsches Studierendenwerk (2020)
First-year students	Number of students in first semester at higher education institutions	Absolute	DZHW: ICEland data basis 601, 80001, 80101, 80601, and 80801
Average study time	Mean of study duration per graduate at higher education institutions	In semester	DZHW: ICEland data basis 34601
HEI financing	Expenditure/income (differentiation according to university finance statistics) of higher education institutions	Absolute	DZHW: ICEland data basis 4104
HEI personnel	Personnel at higher education institutions	Absolute	DZHW: ICEland data basis 60002

Notes: Own illustration.

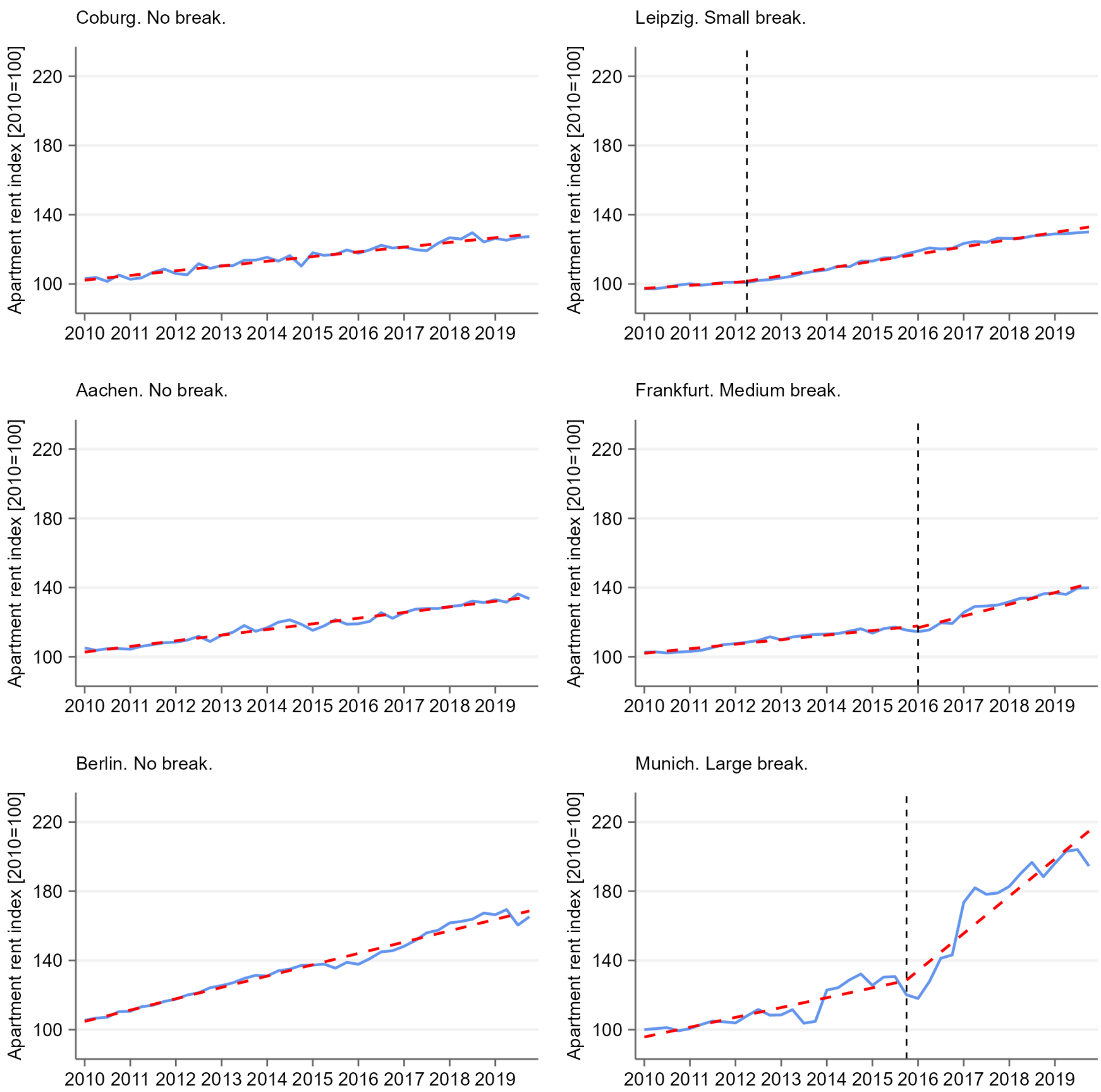
Table A-2: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
Total change apartment rents [%]	1,780	26.597	13.620	4.710	103.107
Total change apart. purch. prices [%]	1,760	51.533	34.820	−18.591	189.628
Total change house purch. prices [%]	1,780	67.300	50.299	2.532	268.819
Apartment rent index (rel. to mean)	1,780	−3.612	21.240	−40.668	119.945
Apartment purch. price index (rel. to mean)	1,768	−11.482	35.416	−83.790	182.220
House purch. price index (rel. to mean)	1,780	21.310	54.669	−67.938	306.621
Number of ads apart. to rent	1,780	4,880.7	10,431.0	255	153,580
Number of ads apart. to purchase	1,780	1,898.2	6,517.7	29	126,871
Number of ads house to purchase	1,780	1,920.2	1,856.1	85	23,279
Number of first-year students	1,780	2,620	3,874	100	35,265
First-year students pc	1,780	11.299	9.961	0.275	68.164
Average study duration [sem]	1,744	9.696	1.665	3.500	14.700
Share fy students from home state [%]	1,780	0.594	0.210	0.086	1.000
Share fy students from home LMR [%]	1,780	0.282	0.160	0.014	0.819
Share fy students from home district [%]	1,780	0.144	0.078	0.000	0.489
Population density	1,780	815.6	817.426	45.889	4,787.8
Share of young population [%]	1,780	8.246	1.732	3.966	14.175
Share of migrants [%]	1,780	10.345	5.424	1.020	29.540
Share of female population [%]	1,780	50.971	0.724	48.760	53.362
Total persons in employment [1,000]	1,780	161.779	197.381	28.700	2,072
Unemployment rate [%]	1,780	6.690	2.961	1.800	16.300
Household income pc	1,780	21,000.4	3,263.2	14,559	42,275
Share of college educated workers [%]	1,780	14.017	5.552	4.492	35.686
Youth employment rate [%]	1,780	37.055	6.949	15.223	54.440
Share of young employed in constr. [%]	1,780	7.005	2.679	2.354	19.591
Share of young employed in FIRE [%]	1,780	3.041	1.260	0.646	9.912
Youth employed in minijobs pc	1,780	2.152	1.056	0.405	6.627
VET applicants with heeq pc	1,780	7.473	3.404	1.700	38.183
Living space pc	1,780	0.044	0.004	0.036	0.055
Share of small apartments [%]	1,780	13.446	5.801	3.545	31.928
Share of big apartments [%]	1,780	38.273	12.726	13.092	72.688
Building permits pc	1,780	3.115	1.949	0.231	15.569
Completed apartments pc	1,780	1.460	1.353	0.000	10.352
Student residence halls	1,397	13.858	17.462	0	160
Places in student residence halls	1,415	1,603.5	2,008.4	3	12,581
Accommodation rate	1,415	10.378	6.324	0.114	123.158
Cafeterias	570	16.188	9.216	2	57
Cafeteria seats	570	4,144	2,207	1,254	13,464
Cafeteria seats per student	570	10.577	2.814	5.400	29.400
Total endowments (HEI) [M]	1,780	59.452	179.502	0.000	2,431.7
Total expenditures (HEI) [M]	1,780	151.023	319.561	0.000	3,724.4
Total personnel (HEI)	1,780	3,677.1	6,399.0	0	45,350
Total scientific personnel (HEI)	1,780	2,028.2	3,375.1	0	25,970

Notes: The table shows summary statistics for the main variables used, including the number of observations (N), the mean, the standard deviation (St. Dev.), the minimum value, and the maximum value. Only districts used in the main analysis are included. Summary statistics refer to the short observation period (2010-2019). Data on student residence halls and cafeterias are only available for subsets of districts.

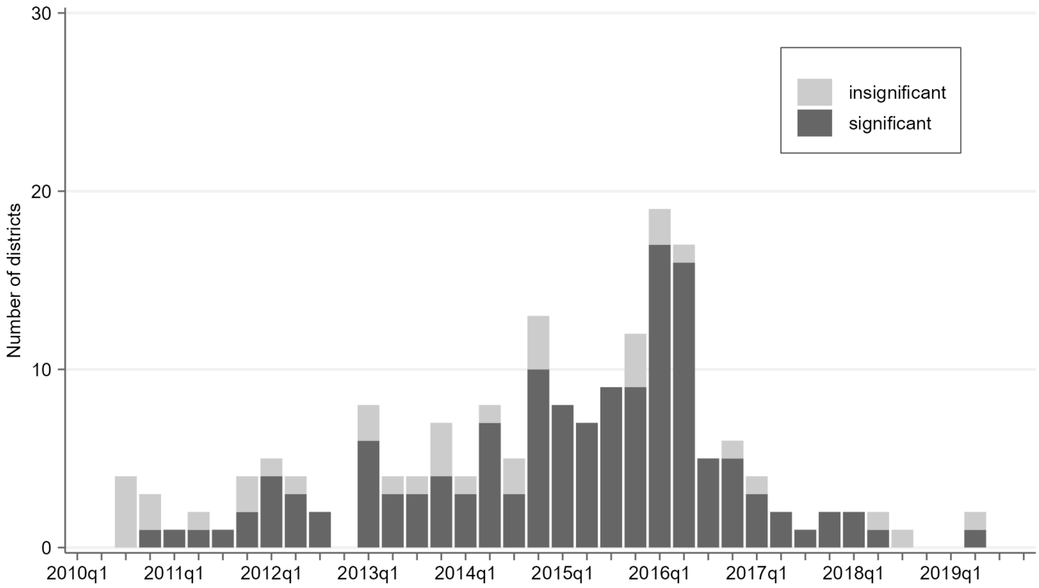
B Estimation of Structural Breaks

Figure B-1: Examples of Variation in Structural Breaks



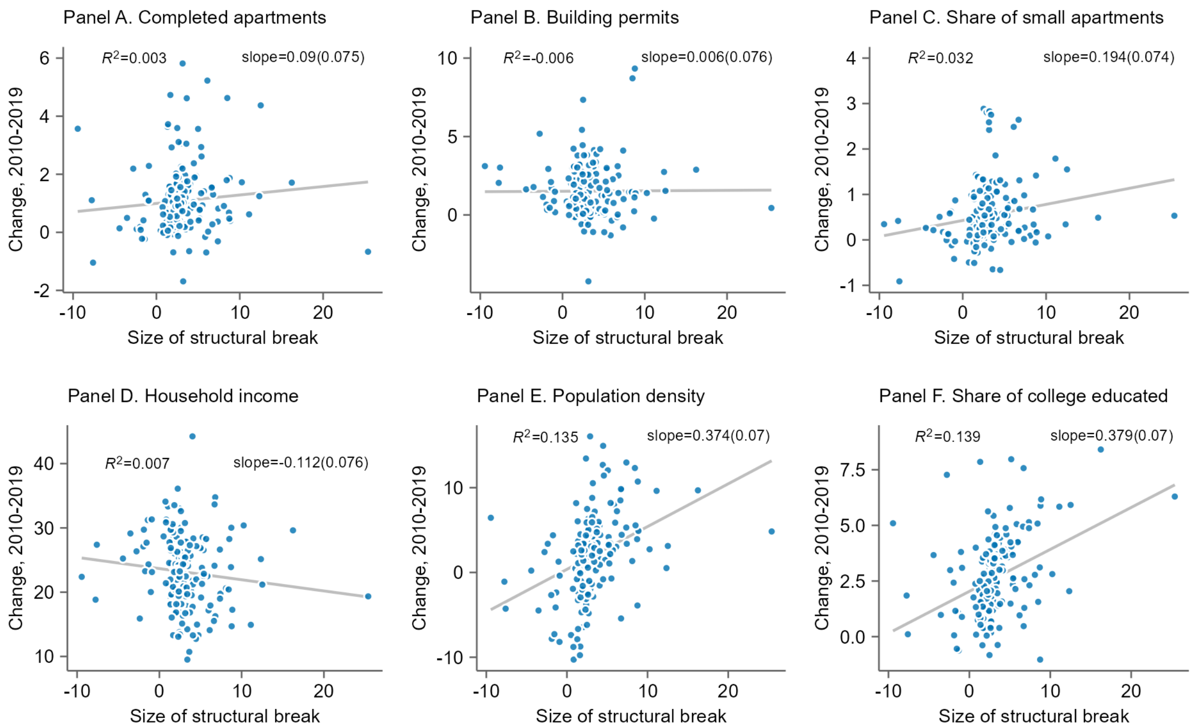
Notes: The figure shows the exemplary evolution of apartment rents (2010=100) for six districts. The solid lines represent the observed apartment rents, the dashed red lines represent the estimated segmented linear relationship, and a vertical dashed line indicates the estimated timing of the structural break. The districts in the first column are examples of relatively small estimated structural breaks, while the districts in the second column show relatively large estimated structural breaks. Apartment rent data are from the RWI-GEO-REDX (Schaffner et al., 2022a).

Figure B-2: Structural Break Timings



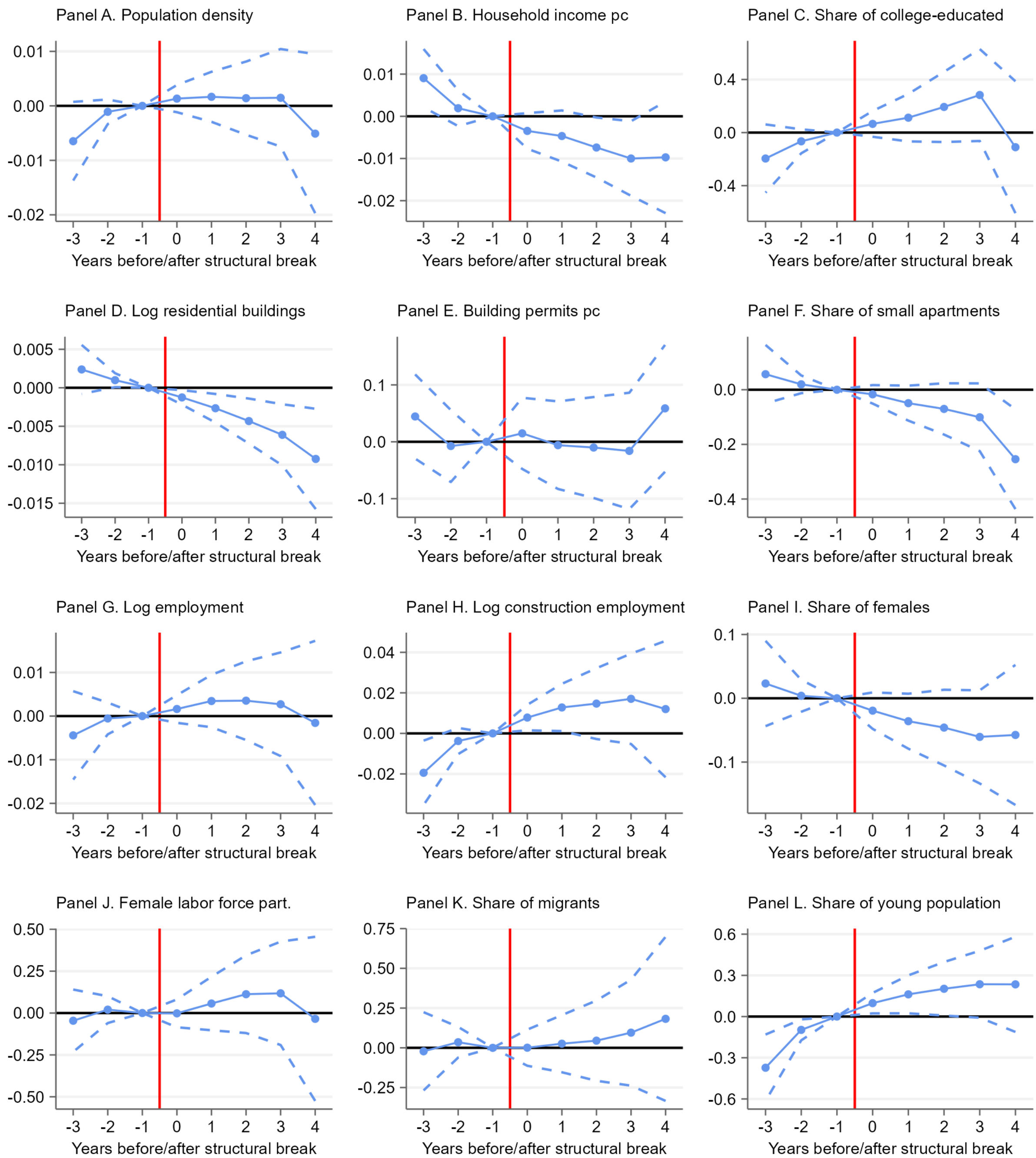
Notes: The histogram shows the number of structural breaks across all year-quarters. Significant (p-value < 0.05) structural breaks are shown in dark gray, insignificant breaks in light gray.

Figure B-3: Regional Fundamentals and Size of Structural Break



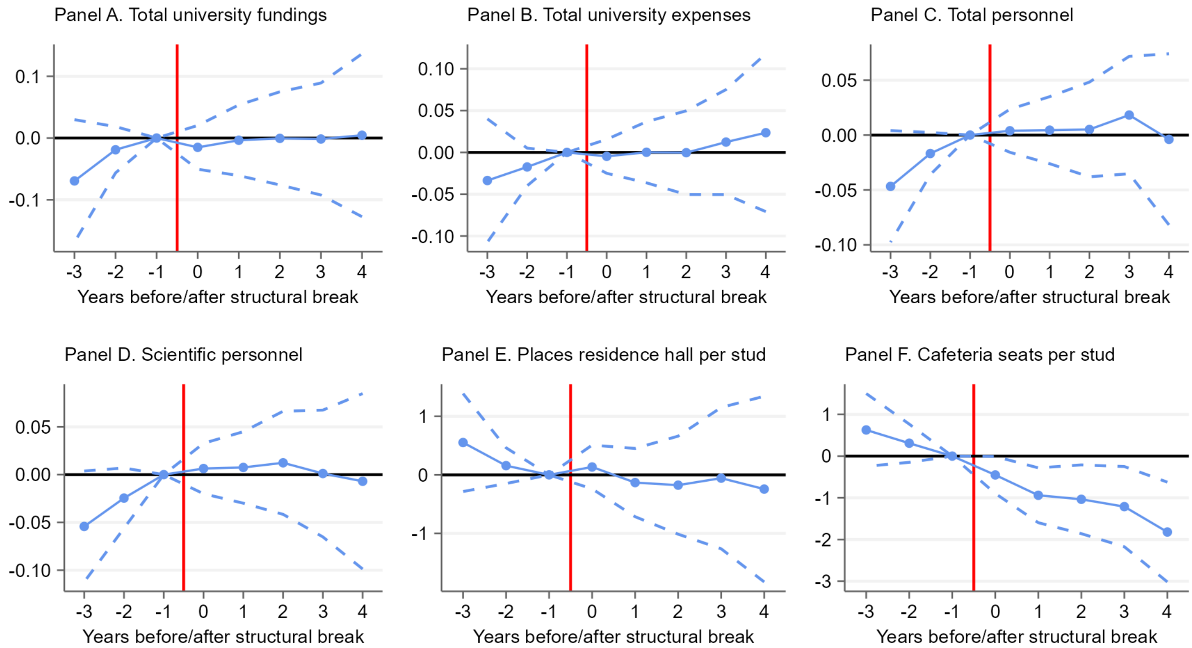
Notes: The figure shows the correlation between several regional fundamentals (y-axis) and the size of the structural break (x-axis). Panel A uses the change in new apartments per capita, Panel B the change in building permits per capita, Panel C the share of small apartments, Panel D the change in household income per capita, Panel E the change in population density, and Panel F the change in the share of college educated workers. All variables are expressed as the total change from 2010 to 2019, given in percent (Panels A, B, D, and E) and percentage points (Panels C and F), respectively. The gray solid line represents a trend line resulting from a linear fit, for which the R-squared and the correlation coefficient with standard errors (in parentheses) are given. Housing price data are from the RWI-GEO-REDX (Schaffner et al., 2022a).

Figure B-4: Regional Factors around the Time of the Structural Break



Notes: The figure shows event study estimates for several regional characteristics around the timing of the structural break. Panel A uses log population density, Panel B log household income per capita, Panel C the share of college-educated workers, Panel D log residential buildings, Panel E the log number of building permits per capita, Panel F the share of small apartments, Panel G log total employment, Panel H log employment in construction, Panel I the share of females, Panel J the share of women in the labor force, Panel K the share of migrants, and Panel L the share of population aged 18-25 years old as the dependent variable. The regressions include indicator variables for each year before and after the year of the estimated structural break, interacted with a dummy of a significant break. The effect in year -1 is normalized to zero. All specifications include year and district fixed effects. The last lag and lead are binned to capture all events before and after, respectively. Robust standard errors are clustered at the district level. 95% confidence intervals are shown.

Figure B-5: HEI Endowment and Amenities around the Time of the Structural Break



Notes: The figure shows event study estimates for several several indicators of endowments of higher education institutions around the timing of the structural break. Panel A uses log total funding, Panel B log total expenditures, Panel C the log total number of personnel, Panel D the log number of scientific personnel, Panel E the log number of places in student residence halls, and Panel F the log number of seats in cafeterias operated by the Studierendenwerk. Data on student residence halls and cafeterias are only available for subsets of districts (see Appendix Table A-2). The regressions include indicator variables for each year before and after the year of the estimated structural break, interacted with a dummy of a significant break. The effect in year -1 is normalized to zero. All specifications include year and district fixed effects. The last lag and lead are binned to capture all events before and after, respectively. Robust standard errors are clustered at the district level. 95% confidence intervals are shown.

Table B-1: Overview of Estimated Structural Breaks

ID	Name	Price Change	Timing	Size	p-value
01001	Flensburg, Kreisfreie Stadt	24.4	2013	3.6	0.000
01002	Kiel, Landeshauptstadt, Kreisfreie Stadt	26.5	2015	2.4	0.000
01003	Lübeck, Hansestadt, Kreisfreie Stadt	25.1	2015	3.0	0.000
01051	Dithmarschen, Landkreis	17.4	2015	2.2	0.000
01056	Pinneberg, Landkreis	26.4	2016	2.9	0.000
01058	Rendsburg-Eckernförde, Landkreis	23.3	2012	4.0	0.000
02000	Hamburg	32.3	2016	3.0	0.003
03101	Braunschweig, Kreisfreie Stadt	33.1	2018	-4.4	0.015
03102	Salzgitter, Kreisfreie Stadt	12.8	2011	2.6	0.000
03103	Wolfsburg, Kreisfreie Stadt	32.1	2015	-2.8	0.171
03153	Goslar, Landkreis	15.3	2013	1.8	0.000
03158	Wolfenbüttel, Landkreis	21.5	2014	1.6	0.000
03159	Göttingen, Landkreis	28.5	2014	3.3	0.000
03241	Region Hannover, Landkreis	33.7	2013	2.5	0.000
03254	Hildesheim, Landkreis	21.4	2015	2.8	0.000
03255	Holzminden, Landkreis	8.7	2014	2.4	0.000
03355	Lüneburg, Landkreis	29.8	2012	3.5	0.000
03359	Stade, Landkreis	23.2	2018	3.5	0.060
03360	Uelzen, Landkreis	20.0	2017	1.6	0.044
03402	Emden, Kreisfreie Stadt	11.2	NA	NA	NA
03403	Oldenburg (Oldenburg), Kreisfreie Stadt	23.1	2016	3.2	0.000
03404	Osnabrück, Kreisfreie Stadt	36.3	2016	3.3	0.000
03405	Wilhelmshaven, Kreisfreie Stadt	15.0	2015	2.0	0.000
03454	Emsland, Landkreis	15.1	2010	6.8	0.585
03460	Vechta, Landkreis	25.2	NA	NA	NA
04011	Bremen, Kreisfreie Stadt	31.4	2015	1.4	0.362
04012	Bremerhaven, Kreisfreie Stadt	21.5	2017	3.6	0.000
05111	Düsseldorf, Kreisfreie Stadt	34.1	2016	3.8	0.000
05112	Duisburg, Kreisfreie Stadt	17.2	2015	2.4	0.000
05113	Essen, Kreisfreie Stadt	23.4	2015	2.9	0.000
05114	Krefeld, Kreisfreie Stadt	20.9	2016	1.4	0.000
05116	Mönchengladbach, Kreisfreie Stadt	19.0	2015	1.9	0.000
05117	Mülheim an der Ruhr, Kreisfreie Stadt	22.7	2016	2.4	0.000
05124	Wuppertal, Kreisfreie Stadt	18.4	2015	1.8	0.000
05154	Kleve, Kreis	18.0	2013	1.6	0.171
05158	Mettmann, Kreis	20.4	2016	2.9	0.000
05162	Rhein-Kreis Neuss	21.8	2016	5.1	0.000
05170	Wesel, Kreis	15.4	2015	1.8	0.000
05314	Bonn, Kreisfreie Stadt	28.8	2016	4.7	0.000
05315	Köln, Kreisfreie Stadt	44.4	2016	5.8	0.000
05334	Städteregion Aachen (einschl. Stadt Aachen)	28.4	2010	4.1	0.748
05358	Düren, Kreis	22.2	2014	1.4	0.000
05362	Rhein-Erft-Kreis	25.6	2015	2.4	0.000
05366	Euskirchen, Kreis	17.0	2017	2.7	0.001
05374	Oberbergischer Kreis	14.2	2015	2.4	0.000
05378	Rheinisch-Bergischer Kreis	20.9	2015	2.7	0.000
05382	Rhein-Sieg-Kreis	21.9	2015	2.0	0.000
05513	Gelsenkirchen, Kreisfreie Stadt	18.5	2014	2.0	0.000
05515	Münster, Kreisfreie Stadt	28.9	2016	4.4	0.000
05554	Borken, Kreis	18.7	2016	1.0	0.004
05558	Coesfeld, Kreis	16.5	2016	2.1	0.000
05562	Recklinghausen, Kreis	17.1	2016	2.6	0.000
05566	Steinfurt, Kreis	17.8	2015	1.4	0.000
05711	Bielefeld, Kreisfreie Stadt	23.4	2011	7.4	0.000
05762	Höxter, Kreis	12.3	NA	NA	NA
05766	Lippe, Kreis	17.2	2015	1.5	0.001
05770	Minden-Lübbecke, Kreis	19.9	2015	2.6	0.000
05774	Paderborn, Kreis	23.2	2012	1.4	0.185
05911	Bochum, Kreisfreie Stadt	21.1	2015	2.5	0.000
05913	Dortmund, Kreisfreie Stadt	31.5	2011	8.1	0.000
05914	Hagen, Kreisfreie Stadt	11.2	2014	1.5	0.000
05915	Hamm, Kreisfreie Stadt	18.4	2015	1.7	0.000

Continued on next page.

Table B-1: Overview of Estimated Structural Breaks

ID	Name	Price Change	Timing	Size	p-value
05954	Ennepe-Ruhr-Kreis	15.1	2015	1.4	0.000
05958	Hochsauerlandkreis	12.4	2014	1.7	0.000
05962	Märkischer Kreis	13.1	2012	2.7	0.000
05970	Siegen-Wittgenstein, Kreis	19.8	2017	1.9	0.000
05974	Soest, Kreis	17.7	2016	1.2	0.010
06411	Darmstadt, Kreisfreie Stadt	34.1	2015	8.8	0.000
06412	Frankfurt am Main, Kreisfreie Stadt	51.0	2016	8.4	0.000
06414	Wiesbaden, Landeshauptstadt, Kreisfreie Stadt	34.4	2016	4.1	0.000
06432	Darmstadt-Dieburg, Landkreis	26.2	2014	3.3	0.000
06433	Groß-Gerau, Landkreis	28.7	2014	1.1	0.077
06434	Hochtaunuskreis	29.0	2016	5.2	0.000
06438	Offenbach, Landkreis	28.3	2016	3.2	0.000
06439	Rheingau-Taunus-Kreis	23.8	2015	1.2	0.000
06440	Wetteraukreis	29.3	2014	3.8	0.000
06531	Gießen, Landkreis	31.5	2014	4.0	0.000
06532	Lahn-Dill-Kreis	18.2	2014	1.6	0.000
06534	Marburg-Biedenkopf, Landkreis	26.1	2013	2.0	0.125
06611	Kassel, Kreisfreie Stadt	34.4	2013	-2.4	0.001
06631	Fulda, Landkreis	33.6	2014	2.9	0.001
06632	Hersfeld-Rotenburg, Landkreis	22.7	NA	NA	NA
06636	Werra-Meißner-Kreis	16.0	NA	NA	NA
07111	Koblenz, Kreisfreie Stadt	31.4	2013	3.4	0.000
07131	Ahrweiler, Landkreis	21.6	2017	2.4	0.000
07134	Birkenfeld, Landkreis	13.2	NA	NA	NA
07137	Mayen-Koblenz, Landkreis	20.0	2014	2.1	0.003
07143	Westerwaldkreis	22.0	2014	2.3	0.000
07211	Trier, Kreisfreie Stadt	18.6	2016	3.9	0.000
07312	Kaiserslautern, Kreisfreie Stadt	21.8	2016	2.4	0.000
07313	Landau in der Pfalz, Kreisfreie Stadt	28.4	2013	2.5	0.080
07314	Ludwigshafen am Rhein, Kreisfreie Stadt	29.6	2016	3.4	0.000
07315	Mainz, Kreisfreie Stadt	37.2	2016	6.8	0.000
07319	Worms, Kreisfreie Stadt	25.1	2013	2.4	0.000
07320	Zweibrücken, Kreisfreie Stadt	14.2	NA	NA	NA
07334	Germersheim, Landkreis	27.5	2013	2.1	0.003
07337	Südliche Weinstraße, Landkreis	23.5	2013	2.0	0.008
07339	Mainz-Bingen, Landkreis	24.4	2012	1.7	0.001
08111	Stuttgart, Landeshauptstadt, Stadtkreis	103.1	2015	25.4	0.000
08116	Esslingen, Landkreis	49.0	2016	8.7	0.000
08117	Göppingen, Landkreis	31.4	2013	3.5	0.000
08118	Ludwigsburg, Landkreis	48.5	2015	7.4	0.000
08121	Heilbronn, Stadtkreis	49.2	2016	6.1	0.000
08126	Hohenlohekreis, Landkreis	26.7	2011	5.4	0.001
08127	Schwäbisch Hall, Landkreis	34.0	2011	4.1	0.065
08128	Main-Tauber-Kreis, Landkreis	17.8	2012	5.5	0.000
08135	Heidenheim, Landkreis	24.5	2015	3.4	0.029
08136	Ostalbkreis, Landkreis	26.9	2011	5.3	0.000
08212	Karlsruhe, Stadtkreis	34.4	2015	6.0	0.000
08221	Heidelberg, Stadtkreis	34.2	2016	11.1	0.000
08222	Mannheim, Stadtkreis	36.1	2015	4.5	0.000
08225	Neckar-Odenwald-Kreis, Landkreis	23.9	NA	NA	NA
08226	Rhein-Neckar-Kreis, Landkreis	26.5	2014	3.1	0.000
08231	Pforzheim, Stadtkreis	29.3	2016	3.7	0.000
08237	Freudenstadt, Landkreis	26.6	2015	3.1	0.000
08311	Freiburg im Breisgau, Stadtkreis	44.7	2016	12.5	0.000
08317	Ortenaukreis, Landkreis	25.5	2014	3.3	0.000
08326	Schwarzwald-Baar-Kreis, Landkreis	27.6	2013	3.5	0.000
08327	Tuttlingen, Landkreis	42.4	2015	2.4	0.250
08335	Konstanz, Landkreis	42.1	2017	5.7	0.010
08336	Lörrach, Landkreis	48.3	2010	10.2	1.000
08415	Reutlingen, Landkreis	31.8	2016	5.4	0.000
08416	Tübingen, Landkreis	35.5	2016	5.0	0.000
08417	Zollernalbkreis, Landkreis	38.7	2010	12.3	0.007

Continued on next page.

Table B-1: **Overview of Estimated Structural Breaks**

ID	Name	Price Change	Timing	Size	p-value
08421	Ulm, Stadtkreis	26.6	2016	5.2	0.006
08426	Biberach, Landkreis	24.9	2012	2.6	0.001
08435	Bodenseekreis, Landkreis	28.3	2016	2.6	0.010
08436	Ravensburg, Landkreis	28.7	2016	3.0	0.000
08437	Sigmaringen, Landkreis	20.2	NA	NA	NA
09161	Ingolstadt	36.7	2016	6.7	0.001
09162	München, Landeshauptstadt	99.5	2015	16.2	0.000
09173	Bad Tölz-Wolfratshausen, Landkreis	33.9	2014	2.7	0.013
09176	Eichstätt, Landkreis	35.7	NA	NA	NA
09177	Erding, Landkreis	35.7	2013	3.1	0.000
09178	Freising, Landkreis	43.3	2013	5.4	0.000
09179	Fürstenfeldbruck, Landkreis	53.7	2016	6.2	0.000
09184	München, Landkreis	69.2	2015	6.6	0.000
09188	Starnberg, Landkreis	47.7	2016	8.9	0.000
09261	Landshut	38.7	2011	2.9	0.198
09262	Passau	44.8	2014	2.4	0.268
09271	Deggendorf, Landkreis	22.5	2013	1.8	0.513
09277	Rottal-Inn, Landkreis	26.6	NA	NA	NA
09361	Amberg	19.1	NA	NA	NA
09362	Regensburg	34.8	2016	7.4	0.000
09363	Weiden i.d.OPf.	14.6	NA	NA	NA
09461	Bamberg	34.6	2016	3.2	0.013
09462	Bayreuth	36.5	2016	3.4	0.002
09463	Coburg	21.8	NA	NA	NA
09464	Hof	20.0	2014	2.8	0.000
09561	Ansbach	37.1	NA	NA	NA
09562	Erlangen	39.4	2016	3.1	0.081
09564	Nürnberg	41.4	2013	4.1	0.000
09571	Ansbach, Landkreis	27.3	2014	2.2	0.000
09661	Aschaffenburg	31.0	2015	2.1	0.000
09662	Schweinfurt	32.0	NA	NA	NA
09663	Würzburg	42.8	2012	2.3	0.805
09761	Augsburg	49.1	2016	5.1	0.000
09763	Kempten (Allgäu)	36.5	2014	4.6	0.000
09775	Neu-Ulm, Landkreis	34.4	2011	2.4	0.680
10041	Saarbrücken, Regionalverband	18.8	2010	-7.8	0.290
11000	Berlin	54.4	2016	1.3	0.229
12051	Brandenburg an der Havel, Kreisfreie Stadt	19.3	2014	2.6	0.000
12052	Cottbus, Kreisfreie Stadt	13.5	2014	-1.3	0.090
12053	Frankfurt (Oder), Kreisfreie Stadt	4.7	2010	-7.6	0.387
12054	Potsdam, Kreisfreie Stadt	28.3	2016	4.5	0.000
12060	Barnim, Landkreis	26.2	2018	3.7	0.000
12061	Dahme-Spreewald, Landkreis	33.5	2017	8.5	0.000
12066	Oberspreewald-Lausitz, Landkreis	11.0	NA	NA	NA
13003	Kreisfreie Stadt Rostock, Hansestadt	18.3	2016	1.4	0.108
13071	Landkreis Mecklenburgische Seenplatte	9.4	2010	6.7	0.423
13073	Landkreis Vorpommern-Rügen	9.2	2018	2.6	0.003
13074	Landkreis Nordwestmecklenburg	9.8	2014	0.7	0.056
13075	Landkreis Vorpommern-Greifswald	9.4	2014	-1.4	0.110
14511	Chemnitz, Stadt	9.4	2016	-1.0	0.000
14522	Mittelsachsen, Landkreis	7.8	2014	0.5	0.671
14524	Zwickau, Landkreis	8.8	2015	1.3	0.008
14612	Dresden, Stadt	27.2	2019	-9.4	0.047
14626	Görlitz, Landkreis	5.8	2012	1.7	0.006
14627	Meißen, Landkreis	7.5	2018	-3.5	0.092
14628	Sächsische Schweiz-Osterzgebirge, Landkreis	15.3	2017	-1.9	0.002
14713	Leipzig, Stadt	31.8	2012	2.4	0.000
15001	Dessau-Roßlau, Kreisfreie Stadt	15.9	2013	-1.9	0.001
15002	Halle (Saale), Kreisfreie Stadt	17.6	2013	0.8	0.127
15003	Magdeburg, Kreisfreie Stadt	15.6	2015	1.8	0.000
15082	Anhalt-Bitterfeld, Landkreis	9.2	2013	0.8	0.420
15085	Harz, Landkreis	8.7	2014	-0.9	0.007

Continued on next page.

Table B-1: Overview of Estimated Structural Breaks

ID	Name	Price Change	Timing	Size	p-value
15088	Saalekreis	13.8	2013	1.4	0.005
15089	Salzlandkreis	11.0	2014	1.6	0.000
15090	Stendal, Landkreis	12.1	2013	0.8	0.350
16051	Erfurt, krsfr. Stadt	21.1	2012	-1.7	0.021
16052	Gera, krsfr. Stadt	9.6	2013	2.5	0.003
16053	Jena, krsfr. Stadt	19.4	2016	3.1	0.138
16055	Weimar, krsfr. Stadt	21.3	2014	-0.9	0.466
16062	Nordhausen, Kreis	7.2	2017	-1.6	0.471
16066	Schmalkalden-Meiningen, Kreis	12.9	2019	8.7	0.082
16070	Ilm-Kreis	13.3	NA	NA	NA

Notes: The table gives an overview of the estimated structural breaks for all districts in our sample, given with the official district ID and name. The total change in rental prices from 2010 to 2019 is also shown.

Table B-2: First-stage Results

	Main		Size>0		p<0.05	
	(1)	(2)	(3)	(4)	(5)	(6)
Size of structural break	2.509***	2.006***	3.247***	2.596***	2.891***	2.246***
	(0.216)	(0.198)	(0.249)	(0.257)	(0.228)	(0.220)
Controls		x		x		x
Observations	178	178	162	162	142	142
F-Statistic	134.416	48.829	169.353	48.410	160.764	51.867
R-squared	0.433	0.587	0.514	0.608	0.535	0.656
Adj. R-squared	0.430	0.575	0.511	0.596	0.531	0.643

Notes: The table shows first stage results for the 2SLS results reported in Table 1 in the main paper. Column (1) and column (2) refer to the main estimates, column (3) and (4) only include positive structural breaks, and column (5) and (6) only significant structural breaks, which are used as a robustness check. The magnitude of the estimated structural break is used as an instrument for the total change in apartment rents over 2010 to 2019. Controls include log population density, the share of college-educated workers, the share of young population, and the share of school leavers with a higher education entrance qualification in 2010. Standard errors are shown in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table B-3: Size of Rental Price Growth Change around Structural Break

	Rental Price Growth Rate			
	Positive Breaks (1)	Positive Breaks (2)	Negative Breaks (3)	Insignificant Breaks (4)
Relative Year = -3	0.048	-0.529	-1.106	1.555
	(0.286)	(0.406)	(1.460)	(1.593)
Relative Year = -2	1.029**	0.518	0.047	2.151*
	(0.457)	(0.407)	(1.764)	(1.064)
Relative Year = -1	-	-	-	-
Relative Year = 0	-0.419	-0.221	0.352	-0.953
	(0.383)	(0.404)	(1.227)	(0.825)
Relative Year = 1	4.246***	3.875***	-0.772	1.191
	(0.580)	(0.653)	(1.198)	(1.374)
Relative Year = 2	3.975***	3.820***	-0.534	1.530
	(0.489)	(0.485)	(1.513)	(1.821)
Relative Year = 3	2.247***	2.599***	-1.505	-0.360
	(0.298)	(0.646)	(1.979)	(2.236)
Relative Year = 4	2.410***	3.066***	0.759	-0.542
	(0.340)	(0.874)	(2.375)	(3.488)
District FE	x	x	x	x
Year FE		x	x	x
Observations	1307	1307	147	261
R-squared	0.311	0.382	0.320	0.271
Adj. R-squared	0.228	0.302	0.130	0.126

Notes: The table shows estimates for rental price growth rates around the time of the structural breaks. Columns (1) and (2) use only positive and significant breaks, column (3) only negative breaks, and column (4) only insignificant breaks. The sample period in each district is restricted to five years before and six years after the estimated structural break (if available). The last lag and lead are binned to capture all events before and after, respectively. Robust standard errors are clustered at the district-level and shown in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

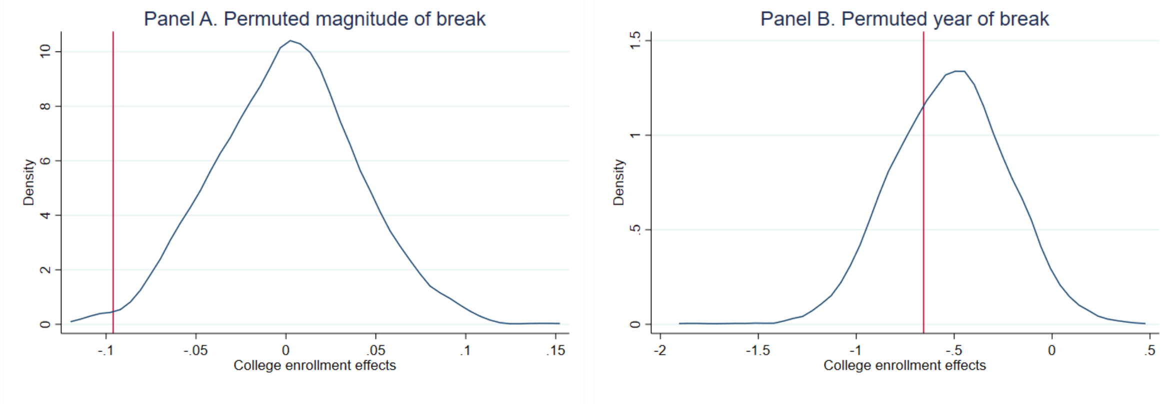
Table B-4: Balancing Table

	Size of structural break		
	All (1)	Positive (2)	Significant (3)
First-year students pc, 2010	-0.028 (0.045)	0.019 (0.038)	-0.003 (0.043)
Unemployment rate, 2010	0.136 (0.194)	-0.059 (0.167)	0.183 (0.186)
Log household income pc, 2010	12.199*** (3.104)	6.322** (2.653)	11.997*** (2.976)
Log population density, 2010	-0.438 (0.444)	-0.416 (0.380)	-0.091 (0.426)
Share of young population, 2010	0.455** (0.196)	0.078 (0.168)	0.281 (0.188)
Share of school leavers with heeq, 2010	-0.051 (0.040)	-0.039 (0.033)	-0.042 (0.039)
Share of college-educ. workers, 2010	0.063 (0.070)	0.180*** (0.059)	0.085 (0.067)
Share of women in labor force, 2010	-0.015 (0.070)	0.019 (0.061)	-0.012 (0.067)
Log living space pc, 2010	-8.383* (4.546)	-11.933*** (3.888)	-7.635* (4.359)
Share of small apartments, 2010	0.062 (0.085)	-0.050 (0.073)	0.009 (0.082)
Building permits pc, 2010	0.304 (0.227)	0.094 (0.188)	0.178 (0.218)
Observations	178	162	178
R-squared	0.304	0.368	0.292
Adj. R-squared	0.258	0.322	0.245

Notes: The table reports estimates from regressing the size of the structural break on regional characteristics. All independent variables are measured at their pre-boom levels in 2010. All coefficients represent the effect of a change of one percentage point or of one unit per capita on the size of the structural break in percentage points. Standard errors shown in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

C Additional Results and Robustness Checks

Figure C-1: Randomization Tests Permuting Magnitude and Timing of Rental Price Booms



Notes: The figure shows the kernel density of the estimated DiD effects of rental price booms on college enrollment rates per capita for 1,000 permutation samples which permute the magnitude (Panel A) and the year (Panel B) of the structural break. In Panel A, we allow the magnitude of the permuted structural breaks to vary within a normal distribution around the mean (2.9) and standard deviation (3.4) that we observe in our data and interact it with the actual break year. In Panel B, we allow the permuted year of break to vary within our observation period (2010-2019) and interact it with the actual treatment dummy for a positive and significant structural break. The red vertical lines represent the estimates from the true data. For Panel A, the red vertical line corresponds to the estimate reported in Table 2.

Table C-1: Effects on College Enrollment: Heterogeneity by Area of Study

	Human. (1)	SoSci (2)	Sciences (3)	Engineer. (4)	Health (5)
Panel A. OLS estimates.					
Δ Apartment rents, 2010-2019	-0.004	-0.008	-0.007	0.002	-0.004
	(0.006)	(0.010)	(0.006)	(0.011)	(0.003)
Observations	178	178	178	178	178
Mean level 10	1.686	3.215	1.541	1.774	0.350
Panel B. 2SLS estimates.					
Δ Apartment rents, 2010-2019	-0.017*	-0.015	-0.027**	-0.003	-0.017***
	(0.010)	(0.017)	(0.011)	(0.018)	(0.006)
Observations	178	178	178	178	178
Mean level 10	1.686	3.215	1.541	1.774	0.350
Panel C. DiD estimates.					
Post $\times$ magnitude struct. break	0.003	-0.020	-0.049***	-0.023	-0.017
	(0.017)	(0.029)	(0.016)	(0.020)	(0.017)
Observations	2136	2136	2136	2136	2136
Mean level	1.598	4.035	1.520	2.747	0.468

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by area of study. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-2: Effects on College Enrollment: Heterogeneity by Degree Types

	BA/Dipl (1)	Teaching (2)	State Ex. (3)
Panel A. OLS estimates.			
Δ Apartment rents, 2010-2019	0.006	-0.012**	-0.004*
	(0.013)	(0.005)	(0.003)
Observations	178	178	178
Mean level 10	7.337	0.852	0.598
Panel B. 2SLS estimates.			
Δ Apartment rents, 2010-2019	-0.027	-0.023***	-0.012***
	(0.022)	(0.008)	(0.004)
Observations	178	178	178
Mean level 10	7.337	0.852	0.598
Panel C. DiD estimates.			
Post $\times$ magnitude structural break	-0.022	-0.011	-0.005
	(0.027)	(0.012)	(0.006)
Observations	2136	2136	2136
Mean level	8.753	0.801	0.661

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by degree type. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-3: Effects on Youth Marginal Employment

	Marg. Emp
	(1)
Panel A. OLS estimates.	
Δ Apartment rents, 2012-2019	0.007
	(0.015)
Observations	178
Mean level 10	7.497
Panel B. 2SLS estimates.	
Δ Apartment rents, 2012-2019	0.006
	(0.022)
Observations	178
Mean level 10	7.497
Panel C. DiD estimates.	
Post $\times$ magnitude struct. break	-0.033
	(0.028)
Observations	2136
Mean level	7.373

Notes: The table reports estimates of the effect of apartment rents on the share of persons aged under 25 years that are in marginal employment (*Mini-Job*). Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-4: Effects on Total Enrollments and on Subject and Location Switchers

	Total Enrollments		Switchers	
	All	MA	All	BA
	(1)	(2)	(3)	(4)
Panel A. OLS estimates.				
Δ Apartment rents, 2010-2019	-0.004	-0.008	0.015	0.014
	(0.036)	(0.016)	(0.026)	(0.014)
Observations	178	178	178	178
Mean level 10	12.533	1.181	3.426	1.232
Panel B. 2SLS estimates.				
Δ Apartment rents, 2010-2019	-0.097	-0.002	-0.015	-0.013
	(0.060)	(0.026)	(0.042)	(0.023)
Observations	178	178	178	178
Mean level 10	12.533	1.181	3.426	1.232
Panel C. DiD estimates.				
Post × magnitude struct. break	-0.221***	-0.080*	-0.125**	-0.068**
	(0.083)	(0.041)	(0.057)	(0.032)
Observations	2136	2136	2136	2136
Mean level	17.233	3.172	6.236	2.333

Notes: The table shows estimates of the effect of apartment rents on all enrollments. Column (1) uses all enrollments (both first-time and consecutive enrollments), column (2) all MA enrollments, column (3) all first-year students that switch their subject or institution (switchers), and column (4) all switchers that study for a BA degree. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. Enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-5: Effects on College Enrollment: Heterogeneity by District Type

	Rural (1)	Urbanized (2)	Large cities (3)
Panel A. OLS estimates.			
Δ Apartment rents, 2010-2019	-0.079**	-0.039	0.032
	(0.031)	(0.026)	(0.033)
Observations	59	60	59
Mean level 10	6.416	5.522	15.444
Panel B. 2SLS estimates.			
Δ Apartment rents, 2010-2019	-0.111**	-0.126**	-0.065
	(0.050)	(0.050)	(0.058)
Observations	59	60	59
Mean level 10	6.416	5.522	15.444
Panel C. DiD estimates.			
Post × size structural break	-0.181**	-0.104**	-0.017
	(0.078)	(0.041)	(0.047)
Observations	708	720	708
Mean level	8.511	6.805	17.745

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by district type according to the classification by the BBSR. The district types "rural districts with densification tendencies" and "sparsely populated rural districts" are combined into "rural" districts to increase the sample size. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-6: Effects on Mobility of First-Year Students: Heterogeneity by Type of Higher Education Institution

	Outside 200km			50-200km			Within 50km		
	Total	Uni	UAS	Total	Uni	UAS	Total	Uni	UAS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. OLS.									
Δ^{10-19} Rents	-0.019***	-0.009***	-0.012***	0.003	0.000	-0.001	0.012*	0.004	0.005
	(0.005)	(0.003)	(0.004)	(0.006)	(0.005)	(0.003)	(0.007)	(0.005)	(0.005)
Observations	178	178	178	178	178	178	178	178	178
Mean level 10	1.168	0.767	0.347	2.913	1.787	0.987	3.704	1.951	1.621
Panel B. 2SLS.									
Δ^{10-19} Rents	-0.031***	-0.016***	-0.017**	-0.010	-0.014*	-0.002	0.002	-0.010	0.006
	(0.009)	(0.005)	(0.007)	(0.010)	(0.008)	(0.005)	(0.011)	(0.008)	(0.008)
Observations	178	178	178	178	178	178	178	178	178
Mean level 10	1.168	0.767	0.347	2.913	1.787	0.987	3.704	1.951	1.621
Panel C. DiD.									
Post × break size	-0.015	-0.004	-0.008	-0.004	-0.007	0.004	0.008	-0.008	0.020**
	(0.012)	(0.007)	(0.012)	(0.014)	(0.011)	(0.010)	(0.013)	(0.010)	(0.009)
Observations	2136	2136	2136	2136	2136	2136	2136	2136	2136
Mean level	1.368	0.798	0.499	3.309	1.841	1.261	4.389	2.123	2.076

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by region of high school graduation. "Outside 200km" refers to those who graduated outside 200 kilometers of the higher education institution, "50-200km" refers to those who graduated within 50 to 200 kilometers of the higher education institution, and "Within 50km" refers to those first-year students who graduated from high school within 50 kilometers of the higher education institution. Distances are calculated as the distance between the centroid of the district of the higher education institution and the district of the high school graduation. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-7: Effects on College Enrollment: Heterogeneity by East and West Germany

	West (1)	East (2)
Panel A. OLS estimates.		
Δ Apartment rents, 2010-2019	0.019	-0.092
	(0.019)	(0.073)
Observations	145	33
Mean level 10	9.204	8.681
Panel B. 2SLS estimates.		
Δ Apartment rents, 2010-2019	-0.070**	-0.124
	(0.035)	(0.208)
Observations	145	33
Mean level 10	9.204	8.681
Panel C. DiD estimates.		
Post × magnitude structural break	-0.083**	-0.125
	(0.037)	(0.112)
Observations	1740	396
Mean level	10.921	11.329

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by East and West Germany. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C-8: Robustness Check for the Effects on College Enrollment: Alternative Instrument Definitions I

	Main (1)	Max break (2)	Sum breaks (3)	First break (4)
Panel A. 2SLS estimates.				
Δ Apartment rents, 2010-2019	-0.081***	-0.075*	-0.094***	-0.064
	(0.029)	(0.043)	(0.033)	(0.059)
Observations	178	178	178	178
Mean level 10	10.185	10.185	10.185	10.185
Panel B. DiD estimates.				
Post × magnitude struct. break	-0.096***	-0.049*	-0.074**	-0.010
	(0.035)	(0.025)	(0.033)	(0.031)
Observations	2136	2136	2136	2136
Mean level	10.997	10.997	10.997	10.997

Notes: The table presents robustness checks for the 2SLS and DID estimates of the effect of apartment rents on first-time enrollment per capita. Column (1) presents the main results reported in Table 1, column (2) uses only positive breaks, and column (3) only significant structural breaks (all others are set to zero). Panel A presents 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel B presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel B are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-9: Robustness Check for the Effects on College Enrollment: Alternative Instrument Definitions II

	Main (1)	size>0 (2)	p<0.05 (3)	Annual TS (4)
Panel A. 2SLS estimates.				
Δ Apartment rents, 2010-2019	-0.081***	-0.046	-0.090***	-0.079***
	(0.029)	(0.029)	(0.031)	(0.030)
Observations	178	162	178	173
Mean level 10	9.107	9.107	9.107	9.107
Panel B. DiD estimates.				
Post × magnitude struct. break	-0.096***	-0.096**	-0.091**	-0.089***
	(0.035)	(0.038)	(0.038)	(0.034)
Observations	2136	1944	2136	2076
Mean level	10.997	10.997	10.997	10.997

Notes: The table presents robustness checks for the 2SLS and DID estimates of the effect of apartment rents on first-time enrollment per capita. Column (1) presents the main results reported in Table 1, column (2) uses only positive breaks, column (3) uses only significant structural breaks (all others are set to zero), and column (4) identifies structural breaks in annual time series. Panel A presents 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel B presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel B are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-10: Robustness Check: Alternative Outcome Definitions

	Main (1)	Weights (2)	No Av (3)
Panel A. OLS estimates.			
Δ Apartment rents, 2010-2019	-0.020	-0.011	-0.023
	(0.017)	(0.014)	(0.018)
Observations	178	178	178
Mean level 10	9.107	9.107	10.185
Panel B. 2SLS estimates.			
Δ Apartment rents, 2010-2019	-0.081***	-0.054**	-0.097***
	(0.029)	(0.022)	(0.031)
Observations	178	178	178
Mean level 10	9.107	9.107	10.185
Panel C. DiD estimates.			
Post × size struct. break	-0.096***	-0.069**	-0.096***
	(0.035)	(0.027)	(0.035)
Observations	2136	2136	2136
Mean level	10.997	10.997	10.997

Notes: The table presents robustness checks for the OLS and 2SLS estimates of the effect of a change in apartment rents on the change in annual first-time enrollments per capita. Column (1) presents the main results reported in Table 1 and 2, column (2) weights the effect by the size of the population aged 18-25 in 2010, and column (3) uses for Panel A and B the plain change of per-capita enrollment rates (rather than 5-year averages). Panel A and B present OLS and 2SLS results. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. The F-statistic from the corresponding first stage is shown at the bottom of the table. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-11: Robustness Check: Different Aggregation Levels

	Main (KRS) (1)	LMR (2)
Panel A. OLS estimates.		
Δ Apartment rents, 2010-2019	-0.020	0.000
	(0.017)	(0.017)
Observations	178	113
Mean level 13	9.107	5.681
Panel B. 2SLS estimates.		
Δ Apartment rents, 2010-2019	-0.081***	-0.102**
	(0.029)	(0.050)
Observations	178	113
Mean level 13	9.107	5.681
Panel C. DiD estimates.		
Post × magnitude struct. break	-0.096***	-0.087***
	(0.035)	(0.025)
Observations	2136	1389
Mean level	10.997	7.334

Notes: The table presents robustness checks for the 2SLS and DID estimates of the effect of apartment rents on first-time enrollment per capita. Column (1) presents the main results reported in Table 1 and 2 on the district level, and column (2) estimates the effect at the labor market region level according to the delineation by RWI (2018) (variant 1). Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents respectively purchase prices. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-12: Robustness Check: Alternative Time Periods

	2009-2019 (1)	Main (2)	2011-2019 (3)	2012-2019 (4)	2013-2019 (5)
Panel A. OLS estimates.					
Δ Apartment rents, 2010-2019	0.013	-0.020	-0.023	-0.031**	-0.028**
	(0.019)	(0.017)	(0.015)	(0.015)	(0.014)
Observations	173	178	179	180	181
Mean level 10	9.877	10.185	11.812	11.205	11.583
Panel B. 2SLS estimates.					
Δ Apartment rents, 2010-2019	-0.050	-0.081***	-0.075**	-0.084**	-0.079**
	(0.037)	(0.029)	(0.037)	(0.039)	(0.039)
Observations	173	178	179	180	181
Mean level 10	9.877	10.185	11.812	11.205	11.583
Panel C. DiD estimates.					
Post × size struct. break	-0.067**	-0.096***	-0.065*	-0.057*	-0.049
	(0.030)	(0.035)	(0.033)	(0.034)	(0.038)
Observations	2076	2136	2136	2136	2136
Mean level	10.997	10.997	10.997	10.997	10.997

Notes: The table presents robustness checks for the OLS and 2SLS estimates of the effect of a change in apartment rents on the change in annual first-time enrollments per capita. Column (1) presents the main results reported in Table 1 and 2, column (2) to (5) represent subperiods where we allow the structural break only in the specified time interval. Panel A and B present OLS and 2SLS results. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level at start of period" refers to the mean of the outcome variable at the beginning of the respective observation period, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-13: Placebo 2SLS Estimates: Enrollment change 2006-2012

	OLS		IV	
	(1)	(2)	(3)	(4)
Panel A. Total Sample.				
Δ Apartment rents, 2010-2019	-0.005	0.011	-0.020	-0.014
	(0.008)	(0.010)	(0.013)	(0.017)
Observations	178	178	178	178
Mean level 06	9.144	9.144	9.144	9.144
Panel B. Men.				
Δ Apartment rents, 2010-2019	-0.005	0.010	-0.017	-0.011
	(0.009)	(0.011)	(0.013)	(0.018)
Observations	178	178	178	178
Mean level 06	9.288	9.288	9.288	9.288
Panel C. Women.				
Δ Apartment rents, 2010-2019	-0.007	0.010	-0.024*	-0.019
	(0.009)	(0.011)	(0.014)	(0.018)
Observations	178	178	178	178
Mean level 06	8.911	8.911	8.911	8.911
First-stage F-statistic	134.4	48.8	134.4	48.8
Controls		x		x

Notes: The table presents placebo OLS and 2SLS estimates of the effect of a change in apartment rents on the change in annual first-time enrollments per capita. Compared to the main estimates, we use the change in the average enrollment per capita between 2002 to 2006 to the average enrollment rate per capita between 2008 to 2012 as the outcome variable. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. The F-statistic from the corresponding first stage is shown at the bottom of the table. Panels A to C show the results for different demographic groups. Controls include log population density, the share of college-educated workers, the share of young population, and the share of school leavers with a higher education entrance qualification in 2010. "Mean level 06" refers to the mean of the outcome variable at the beginning of the selected time window in 2010. Standard errors are shown in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-14: Heterogeneity by Major (Centralized Admissions)

	Medicine (1)	Pharmacy (2)	Dentistry (3)
Panel A. OLS estimates.			
Δ Apartment rents, 2010-2019	-0.002*	-0.000	-0.000*
	(0.001)	(0.000)	(0.000)
Observations	178	178	178
Mean level 10	0.211	0.053	0.040
Panel B. 2SLS estimates.			
Δ Apartment rents, 2013-2019	-0.011	-0.008	-0.001
	(0.006)	(0.009)	(0.001)
Observations	40	29	33
Mean level 13	0.235	0.064	0.042
Panel C. DiD estimates.			
Post × magnitude struct. break	-0.005	-0.002**	-0.000
	(0.004)	(0.001)	(0.000)
Observations	2136	2136	2136
Mean level	0.221	0.058	0.040

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by major group. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C-15: Heterogeneity by Nationality

	HEEQ German (1)	HEEQ foreign (2)
Panel A. OLS estimates.		
Δ Apartment rents, 2010-2019	-0.002	-0.017**
	(0.013)	(0.008)
Observations	178	178
Mean level 10	7.841	1.265
Panel B. 2SLS estimates.		
Δ Apartment rents, 2010-2019	-0.040*	-0.041***
	(0.022)	(0.014)
Observations	178	178
Mean level 10	7.841	1.265
Panel C. DiD estimates.		
Post × magnitude struct. break	-0.012	-0.084***
	(0.028)	(0.030)
Observations	2136	2136
Mean level	9.114	1.882

Notes: The table shows estimates of the effect of apartment rents on first-time enrollment per capita by educational nationality of first-year students, measured as the country of higher education entrance qualification (heeq). Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-16: Robustness Check: Additional Controls

	Main	+ Stud Dorm	+ G8	+ Fee
	(1)	(2)	(3)	(4)
Panel A. OLS estimates.				
Δ Apartment rents, 2010-2019	-0.020	-0.013	-0.022	-0.012
	(0.017)	(0.021)	(0.017)	(0.018)
Observations	178	138	178	178
Mean level 10	9.107	9.107	9.107	9.107
Panel B. 2SLS estimates.				
Δ Apartment rents, 2010-2019	-0.081***	-0.094**	-0.090***	-0.081**
	(0.029)	(0.036)	(0.030)	(0.032)
Observations	178	138	178	178
Mean level 10	9.107	9.107	9.107	9.107
Panel C. DiD estimates.				
Post × magnitude struct. break	-0.096***	-0.089**	-0.096***	-0.100***
	(0.035)	(0.039)	(0.035)	(0.037)
Observations	2136	1695	2136	2136
Mean level	10.997	10.997	10.997	10.997

Notes: The table presents robustness checks for the 2SLS and DID estimates of the effect of apartment rents on first-time enrollment per capita. Column (1) presents the main results reported in Table 1 and 2 on the district level, and column (2) adds additional controls, that is available places in student dormitories. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents respectively purchase prices. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C-17: Robustness Check: New Establishments and Dual Universities

	Main (1)	+ New Estab (2)	- Dual Uni (3)
Panel A. OLS estimates.			
Δ Apartment rents, 2010-2019	-0.020	-0.026	-0.025
	(0.017)	(0.018)	(0.017)
Observations	178	178	178
Mean level 10	9.107	9.135	8.984
Panel B. 2SLS estimates.			
Δ Apartment rents, 2010-2019	-0.081***	-0.078**	-0.097***
	(0.029)	(0.031)	(0.030)
Observations	178	178	178
Mean level 10	9.107	9.135	8.984
Panel C. DiD estimates.			
Post × magnitude struct. break	-0.096***	-0.070*	-0.111***
	(0.035)	(0.040)	(0.039)
Observations	2136	2136	2136
Mean level	10.997	11.101	10.721

Notes: The table presents robustness checks for the 2SLS and DID estimates of the effect of apartment rents on first-time enrollment per capita. Column (1) presents the main results reported in Table 1 and 2. Column (2) and (3) represent robustness check where we add all institutions of higher education that were opened or closed during our observation period (2) and where we remove students at so-called cooperative state universities that integrate academic studies with workplace training. Panel A and B present OLS and 2SLS results. Both the dependent and the independent variables are measured as the long difference between 2010 and 2019. First-time enrollments are further measured as the five-year average of the previous five years at each endpoint. The magnitude of the estimated structural break is used as an instrument for the change in apartment rents respectively purchase prices. Panel C presents the DiD results, estimated as the interaction of the size of the structural break and a dummy indicating the time after the structural break. "Mean level 10" refers to the mean of the outcome variable at the beginning of our observation period in 2010, and "mean level" to the mean over the entire observation period. Standard errors are shown in parentheses. Those in Panel C are robust and clustered at the district-level. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.