Online Appendix

The Impact of International Students on Housing Markets

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A Detailed Data Description

A.1 Main Variables and Sample Selection

Students. The main source of student enrollment and university-related data used in this paper is the Integrated Postsecondary Education Data System (IPEDS) of the US Department of Education. We initially include all 4-year public, private not-for-profit and private for-profit higher education institutions in the U.S. mainland. The selection returns 3,097 universities with 2016 as the base year. For each one of these universities, we gather data on Fall enrollment of full-time degree seeking undergraduate, part-time degree seeking undergraduate, full time graduate and part-time graduate (graduate programs are degree-granting), both nonresident and total (domestic and international) students. The number of degrees awarded to international and total students and institutional characteristics complement the data retrieved from IPEDS.

We drop institutions with less than 500 students enrolled during Fall 2011 and without at least one international student in any year from 2001-2015. Variables of the resulting 1,370 universities are aggregated to the city level, using the place identifier provided by IPEDS. The city identifiers may not map onto Census Designated Place (CDP) nomenclatures, which requires that we homogenize IPEDS and Census names by hand to match data from different sources.

Population. Local population data for 19,506 incorporated places come from the "*Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2016*" and "*Intercensal Estimates of the Resident Population for Incorporated Places and Minor Civil Divisions: April 1, 2000 to July 1, 2010*" files from the U.S. Census Bureau. We combine both datasets and match city-level population to city-level student data. This results in 953 cities, of which 523 locations have at least 10% of local population made up by students, according to 2011-2015 population and total enrollment averages. Finally, we drop places with less than 100 international students enrolled during Fall 2015, further reducing the sample to 351 places.

Isolation. We then calculate the orthodromic distance using the Haversine formula between each city and the nearest MSA with more than 1 million residents. Only the locations no less than 30 miles away from the nearest large metropolitan area are selected to compose the final sample of 241 college towns.

Prices. The novel FHFA Annual House Price Index (HPI) is obtained at the census tract level and then averaged within each college town to correspond to local house prices. We use state-specific Census Block Assignment Files (BAFs) with 2000 and 2010 definitions that enable connecting census blocks to places. We manually convert blocks into tracts, where the latter supersedes the former as the geographic entity for matching FHFA prices and college towns.

Rents. Main data on rents is obtained from Zillow.com from 2012 onward. We use the Zillow Rent Index (ZRI) which is only available for 200 out of 241 college towns. Alternative rental data corresponds to city-level median gross rents from the 5 percent American Community Survey (ACS) samples 2005-2009 and 2011-2016, obtained from the National Historical Geographic Information System (NHGIS) (Manson et al. (2017)). We use the 2005-2009 sample as equivalent to 2005 and 2011-2016 as 2016 in the regressions with yearly variables. These data are available for all college towns in our sample.

Domestic inflows (instrument). State-of-residence domestic inflows are constructed with IPEDS data on two-year Fall enrollment figures for first-time degree-seeking undergraduate students. For each university in our sample, we categorize students' state of residence when first-admitted. Aggregate inflows are sums across all states of residence in the second inflow variable.

A.2 Dynamic Controls

Income. There are two alternative variables for income. From the main specification, county-level personal income per capita observations come from the Bureau of Economic Analysis (BEA). These data are not available down to the place level, hence we construct college town average income series combining 1 percent American Community Survey (ACS) and 5 percent U.S. Census samples from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. (2017)). We use the MAPLE/Geocorr2k (up to 2011) and MAPLE/Geocorr14 (2012 onward) Geographic Correspondence Engines provided by the Missouri Census in order to determine which fraction of each public-use microdata area (PUMA) should be allocated to a corresponding college town. We then reweight individual total income observations using person weights interacted with the new allocation factor based on puma and college town populations prior to obtaining city averages, similarly to Albouy (2016). Since the IPUMS data is unavailable for 2004, we assume that college town personal income appreciated at the same rate as income per capita in the college town's county since 2000. The BEA county-level and IPUMS constructed college-town series have an average correlation of 0.68 between 2004 and 2015.

Unemployment. The unemployment rate used throughout the paper corresponds to annual average unemployment rates at county level from the Local Area Unemployment Statistics (LAUs), provided by the Bureau of Labor Statistics (BLS).

A.3 Initial Characteristics

Crime. Rates per 100,000 population of violent crime, murder and nonnegligent manslaughter, legacy rape, robbery and aggravated assault are obtained from the FBI's database Uniform Crime Reporting Statistics (UCR). The reported crime data is available at the agency level and covers cities with more than 10,000 people. Whenever observations in 2004 are missing, we use the most recent year prior to 2004 of data available. If a certain city only shows statistics for after 2004, we adjust each series assuming that the state-level change from 2004 to the appropriate year is identical to the city-level growth of the statistic. For example, if data for Carbondale, IL only becomes available in 2010, we use the change in robbery in Illinois from 2004-2010 to project the robbery rate in Carbondale in 2004, given the observed value in 2010. We then use the variation of violent crime in the state in the same period to update Carbondale's 2010 violent crime rate and similarly to all other variables. For college towns with population smaller than 10,000, we combine multiple-year "*Offenses Known to Law Enforcement*" tables adopting the same methodology just described for variables missing in 2004. The violent crime variable encompasses the other offenses (murder, aggravated assault etc.). In 2013, FBI's definition of rape changed from including "forcible" in the offense definition to a broader description to characterize rape. Both revised and previous − denominated "legacy" − rape variables are available for more recent data. We use legacy rape statistics to maintain consistency with previous years.

Natural amenities. County-level Winter average temperature and hours of sunlight (January 1931-1970), and relative humidity during Summer (same period) variables are available at the United States Department of Agriculture (USDA) Economic Research Service (ERS) Natural Amenities Scale dataset. Data on land area (squared miles) is retrieved from the 2016 U.S. Gazetteer Files, from the U.S. Census Bureau. We calculate the distance from each college town to the closest coastal border or Great Lake similarly to the computation of the distance to the nearest 1 million people MSA. Coastline limits are defined in the "*Coastline National Shapefile*" from the U.S. Census Bureau. Based on latitude and longitude information for each college town, we obtain the minimum distance in miles to the coastline (or Great Lake) using the Haversine formula.

Population with college degree. Given by the fraction of a college town's population with bachelor's degree or higher, for individuals of age at least 18. The city-level data is compiled from the 5% 2005-2009 ACS sample, available at IPUMS.

B Tracking International Students in the US

In this Appendix segment, we demonstrate why US Census Bureau microdata is inappropriate to track international students with sufficient yearly variation. In reality, even cross-sectional variation for a given year would produce misleading data.

B.1 Aggregate Student Counts

In Table (B.1), we compare American Community Survey (ACS) 1% samples to official data provided by IPEDS.[1] For brevity, we focus on non-citizen and American individuals who reported being enrolled in college as undergraduate, graduate, and professional students in 2016. The ACS domestic student count in 2016 overestimates the official data by about 7%. This discrepancy could originate from measurement error in self-reported school enrollment, documented as "educational attainment error" in Black et al. (2003). Since the international student population count from ACS is 80% higher than the actual international enrollment, measurement error solely attributed to individual misreporting seems unlikely.

TABLE B.1
Share of International and
Domestic Students in the U.S.

	1% ACS*		ACS 5-year**		Official***	
	2005	2016	2005-2009	2011-2015	2005	2016
Foreign-born students†	14.88%	15.23%	13.58%	14.46%	-	-
Non-citizen students‡	8.21%	7.89%	7.27%	7.59%	3.35%	4.83%
Total students (U.S.)	18,064,063	22,559,830	21,262,793	23,362,075	17,710,798	20,389,307
Domestic students	16,581,003	20,779,859	19,716,988	21,588,894	17,117,486	19,404,503

Notes:
†Foreign-born students include undergraduate, graduate and professional students born abroad from American parents, naturalized American and not citizens.
‡Only undergraduate, graduate and professional students non-American citizens.
*Observations weighted by person weight from the Integrated Public-Use Microdata Series (IPUMS) for each correspondent year. Total students represent the sum of weights for all students across a year.
**Observations weighted by person weight from the Integrated Public-Use Microdata Series (IPUMS) for the 5% ACS 5-year sample. Total foreign-born (not-citizen) students represent the sum of weights for all foreign-born (not-citizen) students across the 5-year period.
***Comparison data uses nationwide Fall enrollment from the Integrated Postsecondary Education Data System (IPEDS), National Center for Education Statistics (NCES). The variable that tracks international students in the IPEDS dataset comprises nonresident alien students, as directly reported by all colleges, universities, and technical/vocational institutions that participate in federal student financial aid programs.

B.2 Countries of Origin

Although IPEDS data lacks individual-level country of origin and where these students locate, there is widely available *national* data from the Institute of International Education (IIE)

[1] We also report ACS 5% samples for comparison purposes.

with annual shares of all countries of origin. These data correspond to administrative information and should accurately reflect countries. In Table (B.2), we select leading countries of origin using 1% samples of the ACS in the Integrated Public Use Microdata Series (IPUMS) for 2005 and 2016 and the IIE data, used the official comparison group. The ACS variable that more closely tracks international students is the indicator for "not a citizen enrolled in tertiary education". The distribution of countries of origin shows striking differences from the comparison data. In 2005, the calculated share of Mexicans studying in the U.S. amounted to 14%, well above the actual 2.3% share. Chinese students, on the other hand, held nearly half of their true national participation. ACS 5% samples yield similar comparisons (see Table (B.3)).

Distortion in the representativeness of countries of origin may explain the acute overestimation from the ACS international student enrollment. International students born in a given country who disproportionately locate in larger metropolitan areas could be sampled more often than subgroups of students who locate in smaller cities such as our college towns. Second, and related, the definition for "non citizens" according to the Census Bureau is not equivalent to visa-holding international students accounted for in the IPEDS and IIE official data. If individuals counted as "non-citizen students" are more likely to live in larger areas, the discrepancy between the ACS and IPEDS data is likely to increase. Individuals mistakenly treated as international students would include, for example, DACA-eligible (Deferred Action for Childhood Arrivals) students. DACA-eligible students in college are estimated as more than 240,000.[2]

[2]For more details, see https://www.migrationpolicy.org/research/education-and-work-profiles-daca-population.

TABLE B.2
INTERNATIONAL STUDENTS: LEADING COUNTRIES OF ORIGIN

2005

Source	ACS 1% sample*	Comparison**		ACS 1% sample	Official
Variable	Foreign-born†	Int'l students		Not a citizen‡	Int'l students
Country	Share	Share	Country	Share	Share
Mexico	12.26%	2.31%	Mexico	13.98%	2.31%
Korea	5.30%	9.44%	Korea	5.85%	9.44%
Philippines	5.24%	0.62%	China	5.78%	11.07%
India	4.94%	14.24%	India	5.71%	14.24%
China	4.48%	11.07%	Philippines	3.30%	0.62%
Vietnam	3.68%	0.65%	Japan	2.96%	7.47%
Germany	3.16%	1.53%	Canada	2.44%	4.98%
Canada	2.39%	4.98%	Haiti	2.31%	0.18%
Japan	2.34%	7.47%	Colombia	2.22%	1.30%
Jamaica	2.31%	0.77%	Taiwan	2.05%	4.59%
Total	2,688,788	565,039	Total	1,482,810	565,039

2016

Source	ACS 1% sample	Comparison		ACS 1% sample	Official
Variable	Foreign-born	Int'l students		Not a citizen	Int'l students
Country	Share	Share	Country	Share	Share
Mexico	12.87%	1.60%	Mexico	15.10%	1.60%
China	9.96%	31.47%	China	15.09%	31.47%
India	6.48%	15.89%	India	8.10%	15.89%
Philippines	4.11%	0.28%	Korea	4.05%	5.84%
Korea	3.63%	5.84%	Saudi Arabia	2.79%	5.87%
Vietnam	2.90%	2.05%	Philippines	2.30%	0.28%
Germany	2.48%	0.97%	Vietnam	2.11%	2.05%
Colombia	2.12%	0.75%	Canada	2.10%	2.58%
Haiti	2.12%	0.09%	Brazil	1.87%	1.86%
Canada	2.06%	2.58%	Haiti	1.69%	0.09%
Total	3,435,436	1,043,839	Total	1,779,307	1,043,839

Notes:
†The foreign-born variable includes undergraduate, graduate and professional students born abroad from American parents, naturalized American and not citizens.
‡Non-citizens are constituted as only undergraduate, graduate and professional students non American citizens.
*Observations weighted by person weight from the Integrated Public-Use Microdata Series (IPUMS) for each correspondent year. Total foreign-born (not-a-citizen) students represent the sum of weights for all foreign-born (not-a-citizen) students across a year.
**Comparison variable uses total international enrollment in tertiary education data from the Institute of International Education (IIE).

TABLE B.3
LEADING COUNTRIES OF ORIGIN
(ACS 5% 5-YEAR DATA)

2005-2009

Country	ACS* (Foreign-born)†	Country	ACS (Not a citizen)‡
Mexico	11.89%	Mexico	13.58%
India	5.29%	China	6.75%
Korea	5.19%	India	6.39%
China	5.14%	Korea	5.79%
Philippines	4.80%	Philippines	3.02%
Germany	3.50%	Canada	2.70%
Vietnam	3.31%	Japan	2.46%
Canada	2.52%	Colombia	2.22%
Jamaica	2.31%	Haiti	2.08%
Haiti	2.13%	Taiwan	2.00%
Total foreign-born	2,887,893	Total non-citizens	1,545,120

2011-2015

Country	ACS (Foreign-born)†	Country	ACS (Not a citizen)‡
Mexico	12.39%	Mexico	14.41%
China	8.28%	China	12.51%
India	5.34%	India	6.22%
Korea	4.47%	Korea	5.38%
Philippines	4.43%	Philippines	2.78%
Vietnam	3.07%	Saudi Arabia	2.40%
Germany	2.94%	Canada	2.22%
Haiti	2.25%	Vietnam	2.09%
Canada	2.18%	Colombia	1.96%
Colombia	2.10%	Haiti	1.92%
Total foreign-born	3,377,430	Total non-citizens	1,773,663

Notes:
†Include undergraduate, graduate and professional students born abroad from American parents, naturalized American and not citizens.
‡Only undergraduate, graduate and professional students non American citizens.
*Observations weighted by person weight from the Integrated Public-Use Microdata Series (IPUMS) for the 5% ACS 5-year sample. Total foreign-born (not-citizen) students represent the sum of weights for all foreign-born (not-citizen) students across the 5-year period.

C Panel Time Series Specification Checks

Another dimension to the first-difference estimator in addition to controlling for unobserved individual-specific effects is to rule out the possibility of spurious regression. That is achieved if the dynamic variables in the panel are stationary in first-differences. We conduct a series of tests to check whether our data present unit roots.

We first test for cross-sectional dependence in the panel of the following form:

$$p_{k,t} = \alpha_k + \boldsymbol{\beta}'_k \boldsymbol{x}_{k,t-q} + u_{k,t} \tag{1}$$

where $p_{k,t}$ is the log housing price in college town k, $k = 1, ..., N$, in year $t = 2005, ..., 2016$, $\boldsymbol{x}_{k,t-q}$ includes the international student inflow share measure, unemployment rate, log population, and log income per capita, with lag $q \in [1, Q]$, and α_k is just a nuisance parameter. Cross-sectional heterogeneity is captured by allowing $\boldsymbol{\beta}_k$ to differ across cities. This is a much more flexible model than fixed effects estimation, for example, which imposes homogeneity constraints on coefficients associated with time-varying regressors, $\boldsymbol{\beta}_k = \boldsymbol{\beta}$, for all k. It can also accommodate $\boldsymbol{x}_{k,t-q}$ with dynamic dependent variables, variables integrated of order 1, and $u_{k,t}$ correlated across k. We then proceed to test for the existence of unit roots.

Table (C.1) displays selected tests of cross-sectional dependence and panel unit root tests. Results in column (2) justify the use of unit root tests that do not assume cross-section independence. Average cross correlation coefficients in column (1) indicate strong correlation across college towns in some variables, specially in variable levels when compared to growth rates. As both income and unemployment data are at county level (in the main specification for income), a disproportional number of same-county college towns may influence testing in these two variables. Nonetheless, a much lower correlation in income growth suggests that the 19 counties with more than one college town do not pose systematic measurement error from less disaggregated variables. The relative coefficient magnitude found for price and income levels, generally aligns with findings in Holly et al. (2010) for US states. Overall, CD tests reject cross-sectional independence in all series and warrants for implementing a robust unit root procedure such as CIPS. In the same vein, year fixed effects could help in alleviating cross-sectional dependence originating from common time effects for inference purposes.

The unit root tests in column (3) confirm stationarity of all variables in first-differences, as well as for the international student share and unemployment rate in levels, except for log income and log population.[3] Although all variables are stationary in second-differences, we still employ first-differencing in our OLS and IV regressions to take advantage of more years of data. Also, over-differencing may introduce moving-average components in the series.

We conclude that the first-difference estimator is appropriate for inference with our data. Moreover, aligned with Mikhed and Zemčík (2009), we reject the presence of a unit root in log house prices, but fail to reject stationarity of log income, which trivially implies that both variables cannot be cointegrated. A final caveat is that the time series dimension (T) in the panel is "small" compared to the number of cross section unities (N). Given the importance of an appropriate time length for stationarity testing, our results should be accepted with caution. In any case, they provide additional support for employing first-difference estimation.

[3] Recall that the international student share is already first-differenced.

TABLE C.1

PANEL CROSS-SECTIONAL DEPENDENCE AND UNIT ROOT TESTS

VARIABLE†	AVERAGE CROSS CORRELATION (1)	Pesaran (2004) CROSS-SECTIONAL TEST (2)	Pesaran (2007) UNIT ROOT TEST‡ (3)
log Price	0.294	166.04***	−1.648
log Income	0.928	523.35***	−1.796
log Population	0.337	190.03***	−1.621
Δ log Price	0.465	250.04***	−2.776***
Δ log Income	0.514	276.33***	−1.389
Δ log Population	0.025	14.17***	−1.680
Unemployment	0.882	497.44***	−2.098***
Int'l Students Share	0.146	82.49***	−2.274***

Notes: (1) Reports average cross correlation coefficients $\widehat{\rho_{k,j}}$, where k and j are college towns, and $k \neq j$, for cross-sectional dependence in panels, given by $[2/N(N-1)]\sum_{k=1}^{N-1}\sum_{j=k+1}^{N}\widehat{\rho_{k,j}}$. (2) The null hypothesis is nonexistence of cross-sectional dependence. Values reported are the CD statistic $[2/N(N-1)]^{1/2}[\sum_{k=1}^{N-1}\sum_{j=k+1}^{N}(T_{k,j})^{1/2}\widehat{\rho_{k,j}}]$, which follows the standardized normal distribution under the null. (3) Panel unit root proposed by Pesaran (2007) that is robust under cross-sectional dependence. The values displayed in the table are CIPS test statistics, $N^{-1}\sum_{k=1}^{N}\widetilde{t_k}(N,T)$, where $\widetilde{t_k}(N,T)$ is the cross-sectional ADF statistic for the k-th college town. The null hypothesis is non-stationarity.

†Price, Income and Population and respective first-differences are log variables.

‡Test specifications for Price, Income, ΔPrice, and ΔIncome include an intercept and a linear trend. The other variables are tested under the existence of an intercept.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

D Additional Stylized Facts

This appendix section introduces supportive evidence on the stylized facts of housing markets in college towns we introduce in the main paper, and discuss additional robust patterns. Table (D.1) shows the housing tenure distribution between native students, international students, and non-students in college towns over time.

TABLE D.1
DWELLING OCCUPANCY IN COLLEGE TOWNS

	Renters		Share of renters in MFH		SFH owners	
	2005	2016	2005	2016	2005	2016
International students‡	91.3%	94.6%	94.6%	92.5%	5.1%	3.1%
Native students	75.3%	79.3%	80.7%	78.5%	19.3%	17.1%
Non-students	34.3%	38.0%	65.4%	64.6%	55.7%	53.0%

Notes: ‡Only undergraduate, graduate and professional students non-American citizens. Observations weighted by city-adjusted person weights from the Integrated Public-Use Microdata Series (IPUMS) for each correspondent year. Weights are adjusted according to the procedure described in Appendix (A).

Next, we show that students live near campus and the consequence of this empirical fact on the structure of housing markets in college towns. We run a series of regressions of the form:

$$\text{Outcome}_{g,k} = \theta \times \ln \text{Dist. Campus}_{g,k} + \delta_k + \varepsilon_{g,k} \tag{2}$$

with the following outcomes: (1) share of student population, (2) home ownership, and (3) share of MFH rentals. We regress each outcome in a census block group g in college town k on the log distance in miles from the university campus to that block group and on a college town fixed effect. Census block groups cluster census blocks that contain between 600 and 3,000 people, and represent the smallest geographic area with these data available from the US Census through the National Historical Geographic Information System (NHGIS).[4]

We manually obtain all census block groups contained in each college town k, and calculate the distance from the centroid of these geographic units to campus. Since we use the main office address listed at IPEDS to pinpoint the center of campus, distances within a city always refer to the same fixed locale. We construct two samples. One uses the 134 college towns from our full sample that contain only one university. In the other sample, we add the remaining college towns with more than one university, taking the city center as the main office address of the largest university.

Regression results are shown in Table (D.2). We start with the relationship between the share of the population living on a block group made up by students and the distance from campus, given in column (1). The strong negative association confirms that students disproportionately locate near campus. Furthermore, homeownership increases as one moves away from the university area (column (2)), and the share of multi-family home rentals increases in

[4]The NHGIS contains block-level averages compiled from individually collected Census responses, therefore providing data that is more spatially granular than the standard decennial Census and American Community Surveys.

TABLE D.2
RELATIONSHIP BETWEEN DISTANCE FROM CAMPUS AND OUTCOMES

	% Student population (1)	Home ownership (2)	% MFH rentals (3)	Δ Rent per BR (4)
College towns with one university				
ln Dist. from campus	−0.206***	0.163***	−0.052***	−0.016***
	(0.009)	(0.008)	(0.008)	(0.007)
College town FE	X	X	X	X
R-squared	0.58	0.29	0.18	0.14
Observations (Block groups × college towns)	2958	2921	2759	2642
All college towns				
ln Dist. from campus	−0.194***	0.163***	−0.145***	−0.020***
	(0.007)	(0.007)	(0.007)	(0.004)
College town FE	X	X	X	X
R-squared	0.53	0.26	0.25	0.12
Observations (Block groups × college towns)	8509	8440	8439	9287

Notes: Each column shows regressions of the form $\text{Outcome}_{g,k} = \theta \times \ln \text{Dist. Campus}_{g,k} + \delta_k + \varepsilon_{g,k}$. Standard errors in parentheses are clustered at the college-town level. In specification (1), we regress the share of each block group's population in 2016 composed of college, graduate or professional students on the log distance in miles from that block group to the university's main office address. In (2), the outcome is the number of owner-occupied dwellings in 2016 divided by total dwellings. In (3), the share is with respect to multi-family rentals. Outcome (4) tracks log changes of rents from 2000 to 2016. We calculate the rent per number of bedroom by dividing the midpoint of the average gross rent paid by the number of bedrooms in that unit. Data is compiled from the National Historical Geographic Information System (NHGIS). Monocentric college towns showed on the first panel are those with only one university in our sample. The second panel includes all 241 college towns, including those with more than one university. In such cases, we take the distance of each census block group to the main office address of the largest university in the college town.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.

the opposite direction. Consistent with the fact that students rent MFHs, areas with greater student density also concentrate MFH rentals.

International students pay higher rents than native students. Although international students compete for the same housing stock with domestic students, they pay higher rents for all multi-family rental types (Table (D.3)), perhaps because they occupy better quality housing. International student rent premiums over domestic students reach as much as 20%, with larger rents per room concentrated in mid- and high-rises. Rents in these dwellings well above multi-family rentals below 20 units reflect the fact that many of these buildings are increasingly accompanied by luxury amenities and high-end finishes, features commonly observed in markets characterized by competition with product differentiation.[5]

TABLE D.3
RENTS IN COLLEGE TOWNS

Rent per room	International students		Domestic students		Non-students	
	2005	2016	2005	2016	2005	2016
SFH	197.5	239.4	170.5	196.9	142.2	165.8
1-family home, attached	208.0	256.7	181.2	225.3	176.5	209.4
2 units	187.7	238.8	188.0	221.5	161.0	198.4
$3-4$ units	226.8	261.4	196.7	236.2	175.4	216.2
$5-9$ units	210.0	290.2	205.8	263.5	181.4	227.3
$10-19$ units	234.9	298.4	215.0	266.4	196.9	252.2
$20-49$ units	276.3	351.6	235.9	297.8	228.3	305.8
> 50 units	288.5	407.6	257.6	360.1	249.0	346.2

Notes: Only undergraduate, graduate and professional students non-American citizens. Observations weighted by city-adjusted person weights from the Integrated Public-Use Microdata Series (IPUMS) for each correspondent year. Weights are adjusted according to the procedure described in Appendix (A).

Rents are higher and appreciate faster near campus. Using our sample of college towns, a regression of log rents on distance predicts an increase of 0.04% in rents for a 1% decrease in the distance to campus. Rents per bedroom within 0.5 mile from campus come at a premium of 8% on average.[6] To verify whether rents also increase faster closer to campus, we run model (2) using change in rent per bedroom from 2005 to 2016 as an outcome. To do so, we convert block group boundaries based on 2000 census definitions to 2010 boundary definitions by determining the fraction of a 2000 block group land area allocated to its 2010 respective definition. Column (4) of Table (D.2) shows that rents grew faster in units closer to campus.[7]

Student segregation predates the international student boom. The residential segregation dynamics of college towns has changed little with increasing international student inflows. Student segregation patterns were well-defined before international enrollment was expressive, and although the share of student population near campus increased slightly from 29%

[5]Similar to reported income, self-reported year of construction is prone to large measurement error, particularly for student renters. International students live in rental units one year newer on average than domestic students, but averages display large variability.

[6]Earlier work by Lewis and Kapp (1994) identified rent gradients around campus in Provo and Logan, Utah.

[7]In unreported regressions, we confirm that rental growth within 2 miles from campus was caused by international students by using a long-differences specification.

to 31% over 2000-2016, the change was mainly driven by increased enrollment, and not necessarily nonstudent population decline. Our data shows no evidence of student outflows from the city center toward farther areas, and even of nonstudents within 2 miles from campus. An exception is within census block groups less than 0.5 mile away from campus. In these areas, nonstudent population declined by 8% from 2000 to 2016, and the share of student population jumped from 63% to 68%. This appears to be the area where single-family conversion was more pronounced, which we confirm later in the paper. Thus, (native) students and nonstudents already segregated when the international student density was near zero. Students may prefer to live near campus due to heavy reliance on public transportation, leveraged by multiple daily "commutes", and proximity to local student amenities, such as bars, restaurants, and college facilities. Intuitively, these preferences should not be weaker for internationals, which implies that they are at least as likely as native students to live near campus. Conversely, nonstudent *renters* have little incentive to pay a distance premium for nearby campus units or to occupy dwellings usually supplied to students.

E Detailed Robustness and Sensitivity Checks

One of the identifying assumptions we make in our national-share instrument is that international student enrollment in the base year 1996 is not driven by omitted variables that will affect house prices in the future. While this exclusion restriction is not directly testable, we can test its plausibility by assessing the balance of the historical international share across potential cofounders (Goldsmith-Pinkham et al. (2018)). We explore the relationship between the share of international students coming to each college town of the total enrollment of international students into the US in 1996, and local characteristics that may be correlated with the future evolution of house prices. This analysis is useful because it provides descriptive evidence of which channels could be problematic for the exclusion restriction.

TABLE E.1
INSTRUMENT SHARE AND LOCAL CHARACTERISTICS

$\left(\frac{\text{International}_{k,1996}}{\sum_k \text{International}_{k,1996}}\right)$	
Log income (1996)	0.00185
	(0.001)***
Log population (1996)	−0.00005
	(0.000)
Unemployment rate (1996)	−0.00001
	(0.000)
Log college town area	0.00044
	(0.000)***
Log July humidity	−0.00019
	(0.000)
Log January temperature	−0.00022
	(0.000)
Observations	241
R-squared	0.09
F	4.95
P	0.000

Notes: OLS results of a model regressing the historical share of international students (computed as the enrollment of international students in 1996 to college town k divided by the national international student enrollment in the same year) on the covariates: college town population growth, unemployment rate, log difference of personal income, and weather attributes. There are 241 college towns. Standard errors clustered at city level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

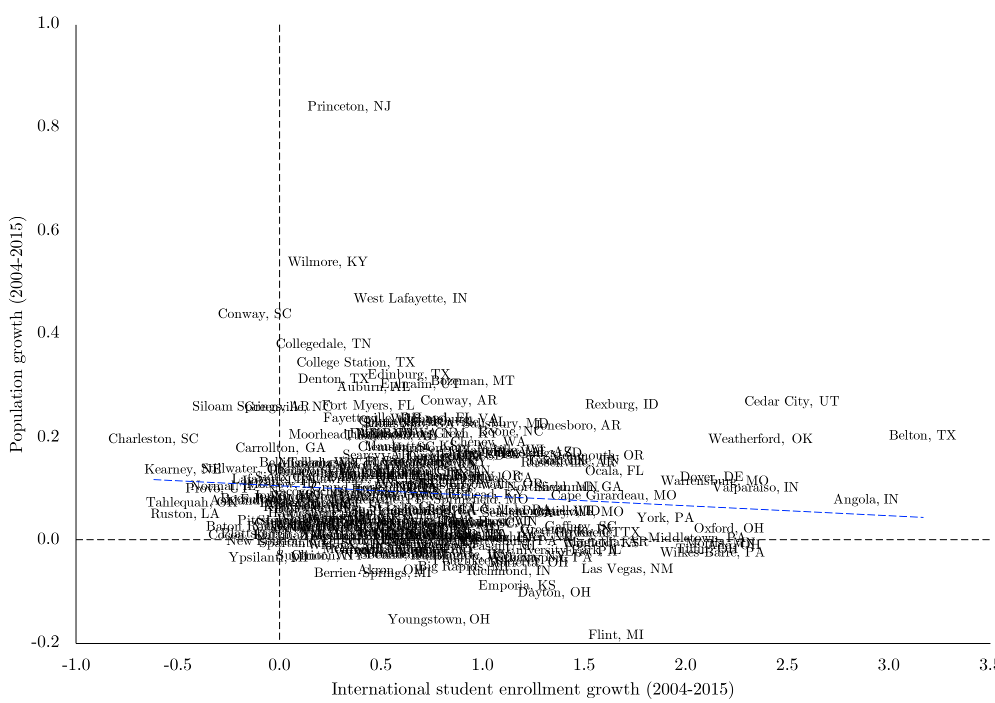
The correlation of the historical share of international students for each college town

$$\left(\frac{\text{International}_{k,1996}}{\sum_k \text{International}_{k,1996}}\right)$$

with city characteristics in the base year reflects the cross-sectional variation that our instrument uses. Finding a high correlation between the 1996 city-share of students from abroad and confounding factors might imply the presence of omitted variables. Table (E.1) shows the relationship between 1996 city characteristics and the city share of international students studying in the US in the same year. The R^2 is fairly low: we can explain only 9% of the variation in the historical international share with the set of covariates. While income and city area are statistically correlated with the share, suggesting that foreign students are concentrated in cities with higher income and fewer housing supply restrictions, the estimated coefficients are very small.

Robustness. There may exist other reasons contributing to price and rent growth in college towns. For example, universities could respond to falling state appropriations by not only recruiting more foreign students, but also out-of-state candidates who pay higher tuition rates than in-state students. Moreover, unobservable characteristics that may make a certain college town or university more attractive to international students might also be valued by domestic students, driving inflows from within the US and from abroad. Perhaps domestic enrollment increases as a response to higher foreign student enrollment, as in Shih (2017). We bring these alternative explanations to the center of our analysis now and test the robustness of our previous results.

While the growth in international enrollment during the last decade has been unprecedented, one might still worry that our previous estimates may be extraneously picking up growth of domestic students or overall population. Figure (E.2) shows a positive relationship between international and domestic enrollment growth, albeit in the majority of college towns international enrollment grew faster in our study period.



Notes: Data description in Appendix (A).

FIGURE E.1

RELATIONSHIP BETWEEN POPULATION AND INTERNATIONAL ENROLLMENT GROWTH

Following the same approach in our main model (equation (1)), we test how including domestic students, out-of-state undergraduate students, or population growth changes our results. We first construct a domestic student inflow measure and add it to our baseline model. Column (1) of (E.2) shows that the previous estimate of the international inflow impact remains practically unchanged and the coefficient on domestic inflows is not different from zero.

TABLE E.2
FALSIFICATION TESTS
MAIN MODEL

	Δ Price$_{t\longrightarrow(t+1)}$							Δ Price$^{\textbf{Placebo}}_{t\longrightarrow(t+1)}$	
	OLS (1)	OLS (2)	IV (3)	OLS (4)	IV (5)	OLS (6)	IV (7)	OLS (8)	OLS (9)
$\frac{\Delta\text{International}_{(t-1)\longrightarrow t}}{\text{College town population}_{t-2}}$	0.351***	0.332***	0.314***	0.303***	0.311***				0.186
	(0.093)	(0.083)	(0.111)	(0.073)	(0.070)				(0.143)
$\frac{\Delta\text{Domestic}_{(t-1)\longrightarrow t}}{\text{College town population}_{t-2}}$	0.001								
	(0.015)								
$\frac{\Delta\text{Out-of-state}_{(t-1)\longrightarrow t}}{\text{College town population}_{t-2}}$		0.019	0.036						
		(0.035)	(0.055)						
$\Delta\text{International}_{(t-1)\longrightarrow t}$						0.002***	0.002***	0.001	
						(0.001)	(0.001)	(0.001)	
$\Delta\text{Population}_{(t-1)\longrightarrow t}$				*X*	*X*	*X*	*X*		
$t = \{2007, \ldots, 2016\}$ dummies	*X*	*X*	*X*	*X*	*X*	*X*	*X*		
$t = \{1998, \ldots, 2005\}$ dummies								*X*	*X*
Full set of controls	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Year fixed effects	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State fixed effects	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Observations (College towns $\times$ T)	2410	1205	1205	1205	1205				
R-squared	0.41	0.41	0.48	0.48	0.48	0.41	0.41	0.38	0.36

Notes: (1) reproduces the main model in equation (3) including domestic student inflows. Column (2) uses instead out-of-state undergraduate inflows and (3) instruments both international student inflows with the national-share instrument and out-of-state inflows with a shift-share instrument using state of residence. (4)-(7) control for population growth. Columns (8) and (9) run placebo-type regressions where we regress past price growth prior to the international student boom on future international student flows.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

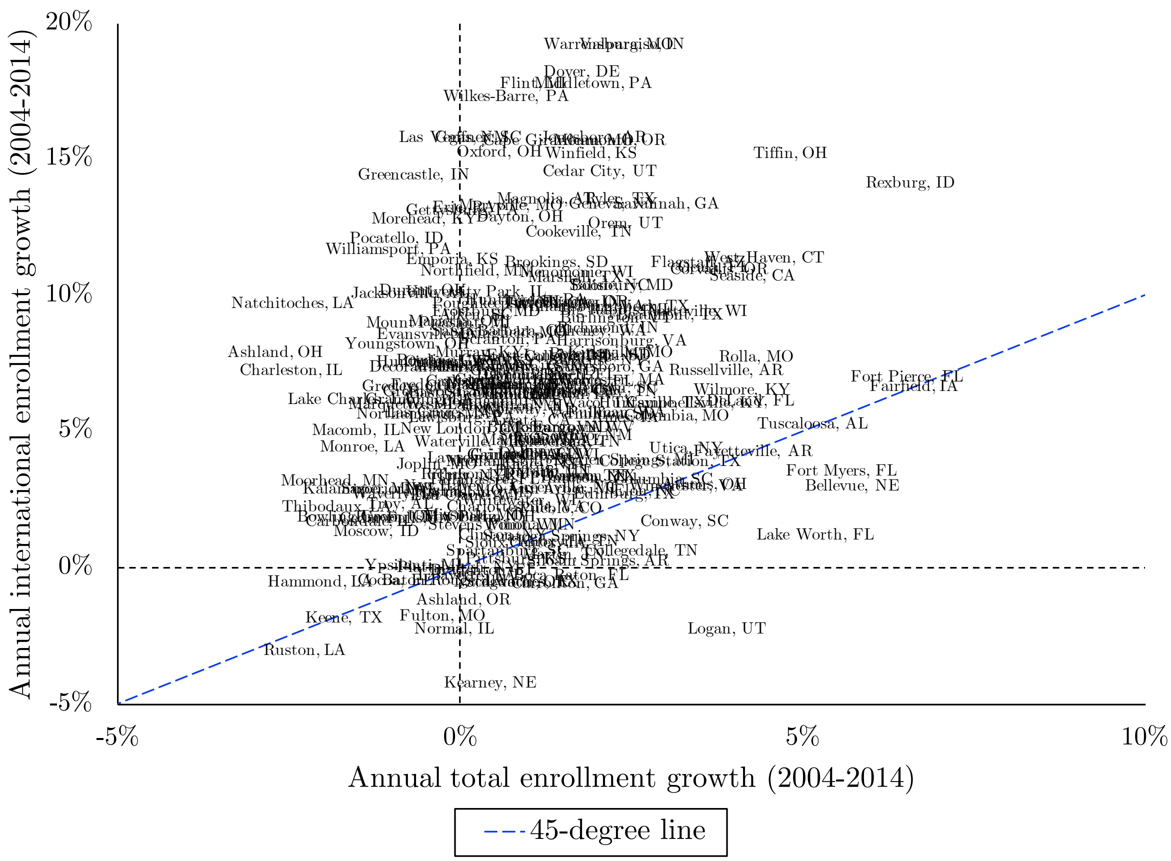
As domestic and international inflows are determined simultaneously, we leverage IPEDS data that allows us to employ a shift-share instrument using variation in the state of residence of freshmen undergraduate students. There is a persistent relationship between students' home state and college choices, beyond obvious patterns of public universities receiving large in-state student contingents.[8] We instrument the domestic undergraduate entry class us-

[8] That might be largely driven by geographic proximity. For example, 4% of 1998 freshmen from Mississippi were attending The University of Alabama in Tuscaloosa, AL. Almost two decades later, this fraction was 6%. Another example: 40% of 1998 freshmen from Hawaii lived in 15 college towns along the West Coast, again a similar fraction in 2016.

ing:

$$\Delta\widehat{\text{Out-of-state}}_{k,t} = \sum_{j \neq j(k)} \frac{\text{Out-of-state}_{j \neq j(k),k,1998}}{\text{Out-of-state}_{j \neq j(k),1998}} \times \Delta\text{Out-of-state}_{j \neq j(k),US,t} \tag{3}$$

where $\frac{\text{Out-of-state}_{j \neq j(k),k,1998}}{\text{Out-of-state}_{j \neq j(k),1998}}$ is the share of the freshmen class from state j, other than the college town's own state, $j(k)$, studying in college town k in 1998, and $\text{Out-of-state}_{j \neq j(k),US,t}$ gives out-of-state student inflows from state j into all college towns at t. Column (2) displays OLS estimates for the international inflow share and the out-of-state inflow variable. Once again, the estimated impact of foreign students remains unchanged and the coefficient of out-of-state inflows is zero. Column (3) instruments each student group inflow and returns similar estimates in magnitude and significance.



Notes: Annualized growth in the enrollment of degree-seeking international and total students in the selected 241 college towns.

FIGURE E.2
INTERNATIONAL AND OVERALL ENROLLMENT GROWTH

Next, we include annual population growth to our main specification to verify whether overall local population growth could be driving our results. Accordingly, controlling for the variable in columns (4) thorough (7) have almost no impact on our main estimate.

Lastly, we conduct a placebo exercise where we regress annual home price changes from 1998 to 2004 on foreign student inflows during the 2005-2015 boom. If college towns receiving larger international student inflows had already been experiencing more accelerated price growth, this exercise would result in significant estimates and indicate the presence of pre-trends. Columns (8) and (9) show no association between higher international inflows and price growth.

Pre-trends in the outcome. When the housing bubble started to collapse around 2007, prices in college towns were more resilient than in the national market. Particularly for those towns with a high participation of international students in total enrollment, the drop in prices was slower and less dramatic. Although influenced by the common national downward trend, the "portfolio" of internationalized college towns excess return over the US benchmark jumped from 0.5% to 10% from 2007 to 2016. Moreover, price trends pre-2006 indicate that college towns were experiencing a slower price increase during the run-up in house prices. This suggests that in the aggregate, returns to housing in college towns have not been secularly higher than the national average.

Even with controls for common economic conditions and initial college town characteristics, local secular trends predating 2005 could result in persistent price behavior that continues into our analysis period. In this case, a potential concern is that we could attribute observable changes in home values to the influx of international students that in reality reflect long-term growth determinants. Our previous placebo exercise does not suggest significant pre-trends, which we confirm again next.

From 1998 to 2004, only 9 out of 241 college towns experienced a drop in home values, and the average nominal price increase reached 35%, against a 43% appreciation at the national level. For the greater part of the housing bubble buildup, prices in college towns were below the national average. To rule out the possibility that college towns coincide with a "sample of winners", in Figure (E.3) we show that real price growth patterns prior to 2005 are negatively associated with price performance from 2005 to 2016.

A simple standardized regression of the log price change in the 2005-2016 period on the price appreciation between 1998 and 2004 returns a correlation of $\widehat{\rho} = -0.35$, suggesting that local price trends from the housing bubble buildup did not predict a subsequent price movement in the same direction. This is consistent with low frequency mean reversion of house prices, an empirical regularity in housing markets (Glaeser et al. (2014)).

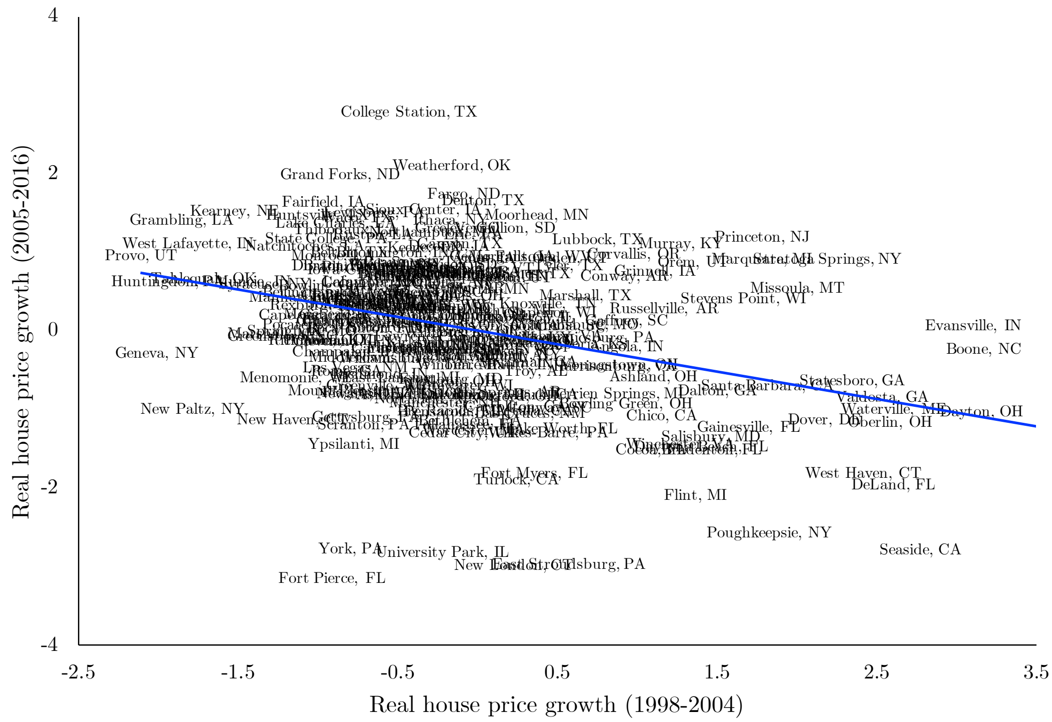
Additional evidence shows that the top decile of college towns experiencing the largest annual price increase during 2005-2016 did not differ systematically from the bottom 10% along several economic indicators (Table (F.4)).

Alternative specifications & sensitivity. We now conduct additional tests to assess the robustness of our main specification. Table (E.3) replicates the main model with home prices as the outcome by first controlling for dorm capacity expansion (column (1)), then using city-level income instead of the county-level variable in the baseline model (column (2)), and finally by including the share of married households in column (3). Then, the following columns remove regression weights and then clustering standard errors at the college town level instead of state. Reported OLS and national-share IV estimates are stable and very similar in magnitude with

TABLE E.3
ROBUSTNESS CHECKS
MAIN MODEL

Δ Price$_{t \longrightarrow (t+1)}$	IV (1)	IV (2)	IV (3)	OLS (4)	IV (5)	OLS (6)	IV (7)
$\frac{\Delta\text{International}_{(t-1)\longrightarrow t}}{\text{College town population}_{(t-2)}}$	0.314***	0.349***	0.354***	0.330***	0.334***	0.353***	0.365***
	(0.089)	(0.075)	(0.079)	(0.074)	(0.078)	(0.104)	(0.129)
	$[0.138, 0.489]^a$	$[0.201, 0.496]^a$	$[0.199, 0.509]^a$		$[0.180, 0.488]^a$		$[0.112, 0.618]^a$
Dorm capacity	X						
Alternative income control		X					
% married households			X				
$t = \{2005, \ldots, 2016\}$ dummies	X	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X
Observations (college towns $\times$ $\sum_t$)	1975	2410	2410	2410	2410	2410	2410
R-squared	0.37	0.34	0.36	0.40	0.40	0.40	0.40

Notes: Column (1) replicates the IV estimator of the impact of international student inflows on home prices with all baseline controls, while including local aggregate annual dormitory capacity. (2) uses city-level income per capita instead of the baseline control county-level income per capita. (3) adds the annual city-level share of married households. (4)—(5) replicates the estimates in Table (II) without weights and (6)—(7) with standard errors clustered at the college town level instead of state level. There are 241 college towns, defined as census places with at least 10% of local population made up by degree-seeking students enrolled in 4-year higher education institutions and no less than 30 miles away from a large MSA (1 million people). Standard errors in () are clustered at the state level. International student inflows (normalized by the local population) are instrumented as described in the main text.
[a]Denotes two-step weak-instruments-robust confidence set from Andrews (2018).
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.



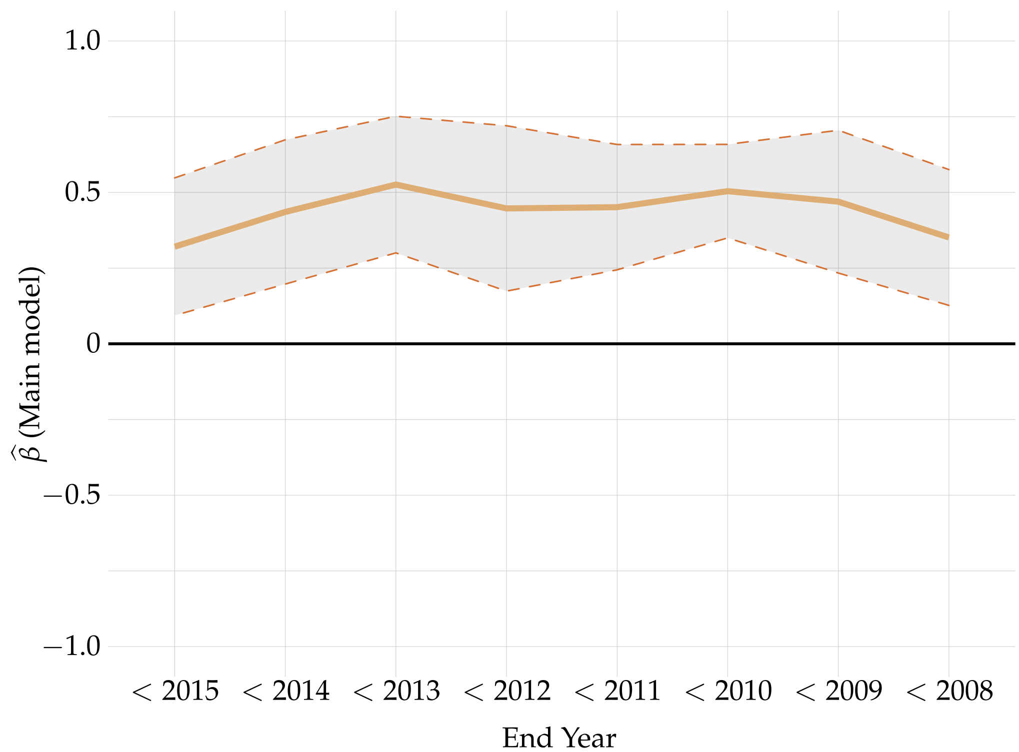
Notes: The figure shows how well the pre-period real price growth (1998-2004) in college towns predicts subsequent real price variation between 2005 and 2016. All variables are normalized to a SD of 1, so that the coefficient of the fitted line $\widehat{\Delta \ln \text{Price}}_{2016-2005} \approx -0.35 \Delta \ln \text{Price}_{2004-1998}$ represents the correlation between the price growth in both periods. College town housing prices are constructed as described in the main text, deflated with the CPI less shelter.

FIGURE E.3

CORRELATION BETWEEN HOUSING PRICE PRE-TREND AND IN-PERIOD GROWTH

the effects we obtained in Table (II). The same exercise for changes in international enrollment and the country-of-origin instrument yield similar results.

To conclude, in Figure (E.4), we restrict the estimation of our main model to progressively shorter time periods. This goes beyond testing for the sensibility of our estimates to a certain timespan, as it also gives a clean assessment of the international student impact at different stages of the housing cycle. Plotted IV estimates of international inflows divided by local population being by discarding data in 2015 and proceeds until leaving only two estimation years, 2006 and 2007. Strong effects concentrated in “bust-only” years imply that college towns receiving larger international student inflows were better able to insulate their housing markets.



Notes: The figure plots IV estimates of the effects of international student inflows on local home prices (baseline model) obtained by progressively discarding the end year of the sample (e.g., < 2015 discards 2015 and runs the model up to 2014) until running only with two years, 2006 and 2007.

FIGURE E.4
RESTRICTING SAMPLE YEARS
MAIN MODEL

F Appendix Figures and Tables

TABLE F.1
DISTRIBUTION OF 4-YEAR UNIVERSITIES: COLLEGE TOWNS AND U.S.

	College Towns		National	
	Count	%	Count	%
4-year public	126	39%	567	42%
4-year private, not-for-profit	188	58%	759	56%
4-year private, for-profit	10	3%	27	2%
Land-grant	10	3%	63	5%

Notes: There are 324 4-year universities in 241 college towns and 1,353 4-year institutions in the US. Data come from IPEDS. More details on data processing and samples in the main text.

TABLE F.2
LIST OF COLLEGE TOWNS

	College town†	Students (2015)	Inter. students (2015)	Population (2016)	Income per capita (2016 $)	Avg. home value (2016 $)‡	Dist. nearest large MSA (miles)*	Number of universities
1	Ada, OH	2,953	122	5,607	31,940	137,426	71	1
2	Aiken, SC	3,152	125	30,937	39,030	121,116	128	1
3	Akron, OH	21,248	1,294	197,633	46,382	87,811	30	4
4	Albany, NY	19,270	1,608	98,111	56,948	165,624	85	8
5	Ames, IA	35,200	3,860	66,191	38,469	165,753	205	1
6	Angola, IN	1,978	324	8,591	38,033	128,246	97	1
7	Ann Arbor, MI	43,459	6,193	120,782	52,814	285,648	35	2
8	Arcata, CA	8,758	114	17,974	43,573	291,350	209	1
9	Ashland, OH	5,179	222	20,489	34,985	120,891	54	1
10	Ashland, OR	4,983	129	21,639	41,852	269,805	230	1
11	Athens, OH	28,979	1,670	25,341	32,183	113,281	65	1
12	Auburn, AL	27,052	1,408	63,118	34,372	136,721	99	1
13	Baton Rouge, LA	30,272	1,604	227,715	45,248	176,467	72	7
14	Beaumont, TX	14,758	1,287	118,299	41,813	116,644	77	1
15	Bellevue, NE	9,589	482	53,505	45,934	157,165	159	2
16	Bellingham, WA	15,266	155	87,574	44,273	374,846	80	3
17	Belton, TX	3,850	357	20,873	41,380	116,220	57	1
18	Berrien Springs, MI	3,146	637	1,752	44,007	138,783	67	1
19	Bethlehem, PA	9,228	1,230	75,293	48,834	171,894	48	3
20	Big Rapids, MI	13,938	485	10,437	30,441	111,595	52	1
21	Blacksburg, VA	32,606	3,517	45,038	33,650	157,456	141	2
22	Bloomington, IN	42,844	6,201	84,465	37,076	191,726	46	1
23	Boca Raton, FL	31,784	1,484	96,114	71,946	681,073	41	4
24	Boone, NC	17,768	103	18,834	34,069	147,867	82	1
25	Bowling Green, KY	17,872	1,232	65,234	36,505	139,023	59	2
26	Bowling Green, OH	16,474	727	31,588	44,029	131,203	73	1
27	Bozeman, MT	15,091	587	45,250	47,959	340,317	343	2
28	Bradenton, FL	9,014	170	55,687	44,158	200,658	33	1
29	Brookings, SD	11,407	761	23,895	43,111	120,347	179	1
30	Burlington, VT	15,778	586	42,260	56,501	309,520	184	2
31	Campbellsville, KY	2,529	237	11,387	33,504	89,735	67	1
32	Canyon, TX	9,477	281	15,138	45,294	167,942	250	1
33	Cape Girardeau, MO	10,498	987	39,628	41,245	121,881	98	2
34	Carbondale, IL	17,119	1,451	26,179	34,125	83,705	82	1
35	Carlisle, PA	2,381	227	19,162	51,384	140,244	70	2
36	Carrollton, GA	12,390	117	26,562	34,723	131,279	42	1
37	Cedar City, UT	6,823	337	31,223	27,068	185,436	154	1
38	Cedar Falls, IA	11,746	531	41,390	40,837	129,534	175	2
39	Champaign-Urbana, IL	44,644	9,975	128,651	42,829	138,435	115	1
40	Charleston, IL	8,381	289	21,133	36,374	88,221	109	1
41	Charleston, SC	21,091	196	134,385	53,272	273,008	174	6
42	Charlottesville, VA	22,935	1,915	46,912	60,964	331,068	67	1
43	Cheney, WA	11,822	428	12,237	42,028	240,752	222	1
44	Chico, CA	16,996	667	91,567	41,725	241,703	83	1
45	Clemson, SC	22,422	1,514	16,058	34,835	154,748	111	1
46	Cleveland, TN	4,632	326	44,271	37,941	128,784	103	2
47	Clinton, NY	1,861	108	1,878	40,236	153,917	113	1
48	Cocoa, FL	12,266	106	18,102	41,685	154,730	39	1
49	College Station, TX	63,561	5,269	112,141	34,776	202,262	80	1
50	Collegedale, TN	2,989	138	11,437	48,053	189,753	98	1
51	Columbia, MO	49,334	2,635	120,612	43,292	178,573	117	3
52	Columbia, SC	34,419	1,406	134,309	42,245	176,754	83	10
53	Conway, AR	12,521	512	65,300	35,159	132,540	137	3
54	Conway, SC	9,937	125	22,761	33,820	133,566	136	1
55	Cookeville, TN	10,574	825	32,622	37,218	132,409	71	1
56	Corvallis, OR	28,620	2,849	57,110	42,245	288,374	72	1
57	Dalton, GA	4,794	125	34,077	36,068	123,514	78	1
58	Dayton, OH	27,529	3,471	140,489	43,051	66,979	50	4
59	Daytona Beach, FL	35,746	1,567	66,645	38,807	172,907	49	4

60	Decorah, IA	2,286	144	7,918	44,138	140,361	138	1
61	DeLand, FL	4,288	182	31,569	38,807	147,917	34	1
62	Denton, TX	51,900	2,756	133,808	51,332	208,053	36	2
63	Dover, DE	16,137	303	37,786	38,498	159,136	58	3
64	Duluth, MN	14,239	370	86,293	43,126	121,061	136	3
65	Durant, OK	3,616	116	17,583	31,902	71,247	87	1
66	East Lansing, MI	50,248	7,344	48,870	37,952	170,772	62	2
67	East Stroudsburg, PA	6,766	103	10,189	39,104	154,002	64	1
68	Eau Claire, WI	10,419	168	68,339	43,543	146,557	88	2
69	Edinburg, TX	28,510	966	87,650	24,805	62,056	216	2
70	Ellensburg, WA	10,982	342	19,786	40,161	229,635	93	1
71	Elon, NC	6,631	117	10,147	36,246	125,061	54	1
72	Emporia, KS	5,960	497	24,816	34,653	65,194	99	1
73	Ephraim, UT	3,470	106	7,072	25,798	186,778	98	1
74	Erie, PA	11,011	1,395	98,593	40,764	86,423	81	4
75	Eugene, OR	23,714	3,274	166,575	41,027	253,146	104	3
76	Evansville, IN	11,148	470	119,477	42,024	96,808	98	2
77	Fairfield, IA	1,521	1,114	10,206	39,956	102,799	190	1
78	Fargo, ND	14,198	988	120,762	53,662	190,187	215	2
79	Fayetteville, AR	26,410	1,372	83,826	36,776	169,957	193	1
80	Flagstaff, AZ	28,898	1,220	71,459	42,057	255,817	123	2
81	Flint, MI	10,070	812	97,386	37,675	41,224	58	3
82	Fort Myers, FL	25,509	506	77,146	45,768	204,733	100	4
83	Fort Pierce, FL	14,403	196	45,295	36,196	152,447	100	1
84	Fredonia, NY	4,802	140	10,639	36,577	98,396	39	1
85	Frostburg, MD	5,645	121	8,676	38,372	109,815	79	1
86	Fulton, MO	3,079	151	13,103	35,473	137,803	96	2
87	Gaffney, SC	3,029	119	12,920	30,026	82,623	47	1
88	Gainesville, FL	62,910	4,862	131,591	41,008	125,147	61	6
89	Geneva, NY	2,264	134	12,988	49,477	150,413	38	1
90	Gettysburg, PA	2,442	131	7,700	45,853	197,054	50	2
91	Grambling, LA	4,537	161	5,217	36,585	98,469	237	1
92	Grand Forks, ND	14,183	737	57,339	48,566	156,138	272	1
93	Greeley, CO	11,701	261	103,990	42,701	240,125	48	1
94	Greencastle, IN	2,229	176	10,508	34,742	106,854	38	1
95	Greensboro, NC	30,763	936	287,027	43,556	167,618	70	5
96	Greenville, NC	26,947	193	91,495	37,943	109,900	72	1
97	Greenwood, SC	2,648	104	23,320	34,478	110,314	103	1
98	Grinnell, IA	1,663	258	9,151	43,876	147,484	207	1
99	Hammond, LA	12,051	226	20,609	35,833	134,848	45	1
100	Harrisonburg, VA	22,596	493	53,078	36,021	204,582	100	2
101	Hattiesburg, MS	18,232	454	46,926	35,451	127,946	104	2
102	Houghton, MI	7,144	1,159	7,987	33,957	89,740	269	1
103	Huntingdon, PA	1,483	118	6,990	37,077	130,552	105	1
104	Huntington, WV	12,883	521	48,113	38,676	102,047	111	1
105	Huntsville, TX	20,031	359	41,208	25,719	102,378	66	1
106	Iowa City, IA	29,457	3,719	74,398	47,456	222,068	202	1
107	Ithaca, NY	28,540	4,718	30,756	40,763	222,705	75	2
108	Jacksonville, AL	7,556	209	12,657	34,401	108,355	63	1
109	Johnson City, TN	13,902	510	66,677	39,909	148,024	115	2
110	Jonesboro, AR	12,727	755	74,889	35,378	97,568	58	1
111	Joplin, MO	5,931	160	52,195	36,598	113,611	140	2
112	Kalamazoo, MI	23,141	1,627	75,984	44,729	122,160	48	2
113	Kearney, NE	6,458	248	33,520	48,026	119,781	263	1
114	Keene, TX	735	101	6,293	38,247	143,646	40	1
115	Kirksville, MO	9,002	463	17,519	30,177	88,563	131	2
116	Knoxville, TN	28,801	1,210	186,239	46,305	134,339	156	6
117	La Crosse, WI	12,984	210	52,109	45,731	153,663	129	2
118	Lafayette, LA	16,729	622	127,626	47,591	196,490	119	1
119	Lake Charles, LA	7,278	544	76,848	44,743	135,907	133	1
120	Lake Worth, FL	26,351	505	37,812	71,946	209,406	58	1
121	Laramie, WY	12,445	817	32,382	38,898	191,822	114	1
122	Las Cruces, NM	14,851	1,151	101,759	32,852	119,472	317	2
123	Las Vegas, NM	3,394	205	13,285	33,062	154,144	286	1
124	Lawrence, KS	26,798	2,278	95,358	39,440	187,548	38	2
125	Lewisburg, PA	3,578	202	5,699	36,251	179,222	115	1
126	Logan, UT	25,628	753	50,676	33,896	190,643	68	2
127	Lubbock, TX	42,421	3,115	252,506	38,757	115,485	282	3

128	Lynchburg, VA	83,571	1,470	80,212	35,818	152,716	97	4
129	Macomb, IL	11,094	505	18,352	34,587	82,167	130	1
130	Madison, SD	2,221	108	7,425	53,278	116,829	201	1
131	Madison, WI	54,877	5,247	252,551	55,232	233,364	77	8
132	Magnolia, AR	3,831	651	11,601	33,634	80,738	210	1
133	Manchester, NH	61,609	1,212	110,506	56,531	180,807	48	5
134	Manhattan, KS	23,730	1,876	54,983	39,592	136,996	109	2
135	Mankato, MN	14,303	1,006	41,720	41,663	143,072	66	2
136	Marietta, OH	1,300	167	13,650	39,140	101,395	90	1
137	Marquette, MI	8,074	112	20,570	38,387	153,421	244	1
138	Marshall, MN	2,708	185	13,664	44,580	114,031	129	1
139	Marshall, MO	1,405	224	12,897	37,880	91,141	74	1
140	Marshall, TX	2,411	129	23,561	41,146	124,596	143	2
141	Martin, TN	6,380	172	10,768	33,491	99,833	106	1
142	Maryville, MO	6,263	767	11,846	30,591	84,616	87	1
143	Mechanicsburg, PA	3,206	112	9,007	51,384	204,226	67	1
144	Menomonie, WI	9,367	280	16,464	36,411	148,500	67	1
145	Middletown, PA	4,552	486	9,229	47,864	156,531	63	1
146	Missoula, MT	12,442	355	72,364	44,134	266,589	394	1
147	Monmouth, OR	5,418	324	10,174	37,818	260,282	54	1
148	Monroe, LA	7,279	267	49,297	38,217	127,570	214	1
149	Moorhead, MN	7,765	434	42,492	41,173	130,113	212	3
150	Morehead, KY	8,130	167	7,758	28,775	89,430	85	1
151	Morgantown, WV	27,858	2,168	30,855	40,949	142,803	56	2
152	Morris, MN	1,741	184	5,295	48,530	117,613	135	1
153	Moscow, ID	10,082	625	25,322	37,996	194,831	258	2
154	Mount Pleasant, MI	26,364	1,176	26,313	32,728	106,292	63	1
155	Muncie, IN	20,283	580	69,010	34,452	91,942	50	1
156	Murray, KY	9,621	690	19,006	33,745	141,362	91	1
157	Nacogdoches, TX	12,269	118	33,932	33,812	106,860	135	1
158	Natchitoches, LA	7,956	110	18,319	35,543	106,630	192	1
159	New Haven, CT	24,360	2,558	129,934	52,603	178,504	34	4
160	New London, CT	3,415	150	26,984	53,885	179,997	41	3
161	New Paltz, NY	7,550	352	7,046	45,030	230,241	72	1
162	Newark, DE	22,105	2,029	33,398	51,034	273,286	37	2
163	Normal, IL	20,677	332	54,264	45,718	143,914	117	1
164	Northampton, MA	2,867	370	28,483	47,440	313,502	39	1
165	Northfield, MN	5,000	433	20,445	40,167	178,915	37	2
166	Oberlin, OH	2,929	237	8,331	42,089	160,898	31	1
167	Ocala, FL	6,670	104	59,253	34,765	123,115	64	2
168	Ogden, UT	17,483	361	86,701	37,691	195,873	33	2
169	Orem, UT	25,936	601	97,499	36,215	265,693	34	4
170	Oxford, OH	18,664	1,774	22,341	42,620	153,512	31	1
171	Pensacola, FL	20,189	279	53,779	39,582	153,404	176	3
172	Pittsburg, KS	6,851	357	20,366	34,508	87,230	117	1
173	Platteville, WI	8,752	208	12,537	39,588	166,186	132	1
174	Plattsburgh, NY	5,613	310	19,780	40,965	128,660	202	1
175	Pocatello, ID	10,847	1,361	54,746	34,709	138,711	149	1
176	Poughkeepsie, NY	8,518	476	30,267	50,132	214,494	64	2
177	Princeton, NJ	8,552	1,779	31,249	63,237	521,098	38	2
178	Provo, UT	33,469	1,226	116,868	36,215	262,599	38	3
179	Pueblo, CO	10,682	138	110,291	36,148	116,162	103	2
180	Pullman, WA	29,316	2,095	33,282	35,697	198,672	250	1
181	Rexburg, ID	28,457	2,006	28,222	24,054	172,669	212	1
182	Richmond, IN	4,341	223	35,664	37,624	95,818	54	3
183	Richmond, KY	16,010	270	34,652	33,139	107,856	88	1
184	Rohnert Park, CA	9,343	182	42,622	56,567	479,828	42	2
185	Rolla, MO	8,794	1,314	20,075	34,489	106,791	97	1
186	Rome, GA	6,937	118	36,407	36,470	100,022	58	2
187	Russellville, AR	9,662	444	29,583	33,331	101,888	175	1
188	Ruston, LA	9,318	457	22,370	36,585	123,474	234	1
189	Salisbury, MD	8,434	131	33,114	39,722	160,514	84	1
190	San Luis Obispo, CA	20,867	409	47,536	51,442	555,347	159	1
191	Santa Barbara, CA	25,960	2,177	91,930	56,048	1,052,720	87	5
192	Saratoga Springs, NY	13,523	798	27,763	62,295	307,054	106	2
193	Savannah, GA	23,301	2,570	146,763	43,076	147,234	119	6
194	Scranton, PA	8,202	238	77,291	43,616	100,335	99	4
195	Searcy, AR	6,009	294	24,318	32,966	90,361	96	1

196	Seaside, CA	6,862	162	34,312	52,448	687,481	50	1
197	Siloam Springs, AR	2,339	106	16,448	76,554	158,798	175	1
198	Sioux Center, IA	1,430	130	7,501	46,732	161,458	196	1
199	Socorro, NM	2,035	158	8,612	32,608	131,585	300	1
200	Spartanburg, SC	8,255	126	37,876	39,386	126,572	64	4
201	Springfield, MO	25,237	1,502	167,319	40,019	115,785	149	10
202	State College, PA	46,744	6,983	41,992	41,032	248,917	115	2
203	Statesboro, GA	19,669	350	31,419	29,737	93,376	146	1
204	Stevens Point, WI	9,129	141	26,423	42,386	148,260	132	1
205	Stillwater, OK	25,558	1,868	49,504	35,896	104,200	53	1
206	Superior, WI	2,395	182	26,475	38,861	154,046	132	1
207	Syracuse, NY	28,274	4,364	143,378	47,865	105,318	75	4
208	Tahlequah, OK	8,019	135	16,741	29,609	87,777	146	1
209	Tallahassee, FL	61,215	1,962	190,894	40,758	178,248	155	5
210	Terre Haute, IN	15,380	1,221	60,852	35,457	84,963	68	2
211	Thibodaux, LA	5,923	126	14,610	43,752	122,556	46	1
212	Tiffin, OH	4,556	361	17,545	38,203	109,668	80	2
213	Troy, AL	17,640	726	19,191	35,287	86,854	128	1
214	Troy, NY	6,899	1,163	49,702	45,212	199,589	84	2
215	Turlock, CA	9,276	282	72,796	41,299	250,330	58	1
216	Tuscaloosa, AL	36,145	1,276	99,543	35,909	156,443	46	2
217	Tyler, TX	19,413	441	104,798	49,857	141,288	93	4
218	University Park, IL	5,894	389	7,052	56,669	141,544	30	1
219	Utica, NY	7,084	246	60,652	40,236	132,880	120	2
220	Valdosta, GA	11,198	288	56,474	34,088	95,110	103	1
221	Valparaiso, IN	4,486	700	33,104	46,965	180,502	41	1
222	Vermillion, SD	8,741	253	10,844	37,265	167,629	238	1
223	Waco, TX	16,737	678	134,432	38,125	111,252	87	2
224	Warrensburg, MO	13,413	2,690	20,251	33,236	104,067	51	1
225	Waterville, ME	1,857	196	16,406	42,194	121,116	167	2
226	Waverly, IA	1,497	124	10,093	44,514	118,180	161	1
227	Weatherford, OK	4,888	214	11,978	35,834	117,026	66	1
228	West Haven, CT	6,726	1,041	54,516	52,603	240,486	37	1
229	West Lafayette, IN	40,145	9,209	45,872	35,804	163,517	62	1
230	Whitewater, WI	11,823	126	14,517	43,989	183,636	44	1
231	Wilkes-Barre, PA	7,170	295	40,569	41,809	87,088	97	2
232	Williamsburg, VA	8,443	665	15,214	59,632	293,612	44	1
233	Williamsport, PA	6,676	137	28,834	40,185	130,181	133	2
234	Wilmore, KY	3,315	196	6,312	39,551	152,362	66	2
235	Winchester, VA	3,801	157	27,516	46,356	225,993	64	1
236	Winfield, KS	1,430	112	12,284	36,240	67,359	126	1
237	Winona, MN	14,204	384	27,139	44,354	143,036	102	2
238	Worcester, MA	22,121	2,513	184,508	52,320	177,389	37	7
239	York, PA	5,576	161	43,859	45,918	105,921	47	3
240	Youngstown, OH	11,508	266	64,312	40,456	48,944	57	2
241	Ypsilanti, MI	21,148	722	21,018	52,814	184,655	30	1

Notes:
†College towns selected as places for which students comprise at least 10% of total population and the nearest MSA with more than 1 million people is no less than 30 miles away.
‡Average home values are calculated for each city in the following manner: first, we obtain weighted-average home values at the city level from 2000 census data. Weights are adjusted-household factors, where 2000 household weights are adjusted according to the proportion of the city's population in its PUMA. We then capitalize 2000 average home values by the annual FHFA indices used in the paper.
*Large MSAs defined as those with more than 1 million people.

TABLE F.3
FIRST STAGE OF INSTRUMENTS

	Prices (Table (II))		Rents (Table (IV))		Prices (Table (III))	
	$\Delta\text{International}_{k,(t-1)\longrightarrow t}$	$\frac{\Delta\text{International}_{k,(t-1)\longrightarrow t}}{\text{Population}_{k,(t-2)\longrightarrow(t-1)}}$	$\Delta\text{International}_{k,(t-1)\longrightarrow t}$	$\frac{\Delta\text{International}_{k,(t-1)\longrightarrow t}}{\text{Population}_{k,(t-2)\longrightarrow(t-1)}}$	$\text{International}_{k,(t-1)\longrightarrow t}$	$\frac{\text{International}_{k,(t-1)\longrightarrow t}}{\text{Population}_{k,(t-2)\longrightarrow(t-1)}}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{\text{International}}_{k,(t-1)\longrightarrow t}$	0.788***		0.801***			
	(0.037)		(0.050)			
$\frac{\Delta\widehat{\text{International}}_{k,(t-1)\longrightarrow t}}{\text{Population}_{k,(t-2)\longrightarrow(t-1)}}$		0.665***		1.030***		
		(0.122)		(0.120)		
$\widehat{\widehat{\text{International}}}_{k,(t-1)\longrightarrow t}$					0.421***	
					(0.025)	
$\frac{\widehat{\widehat{\text{International}}}_{k,(t-1)\longrightarrow t}}{\text{Population}_{k,(t-2)\longrightarrow(t-1)}}$						0.841***
						(0.111)
Observations ($N \times T$)	2410	2410				
Effective F-statistic	447.87	44.01	402.65	82.04	303.58	64.94
Full set of controls	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X

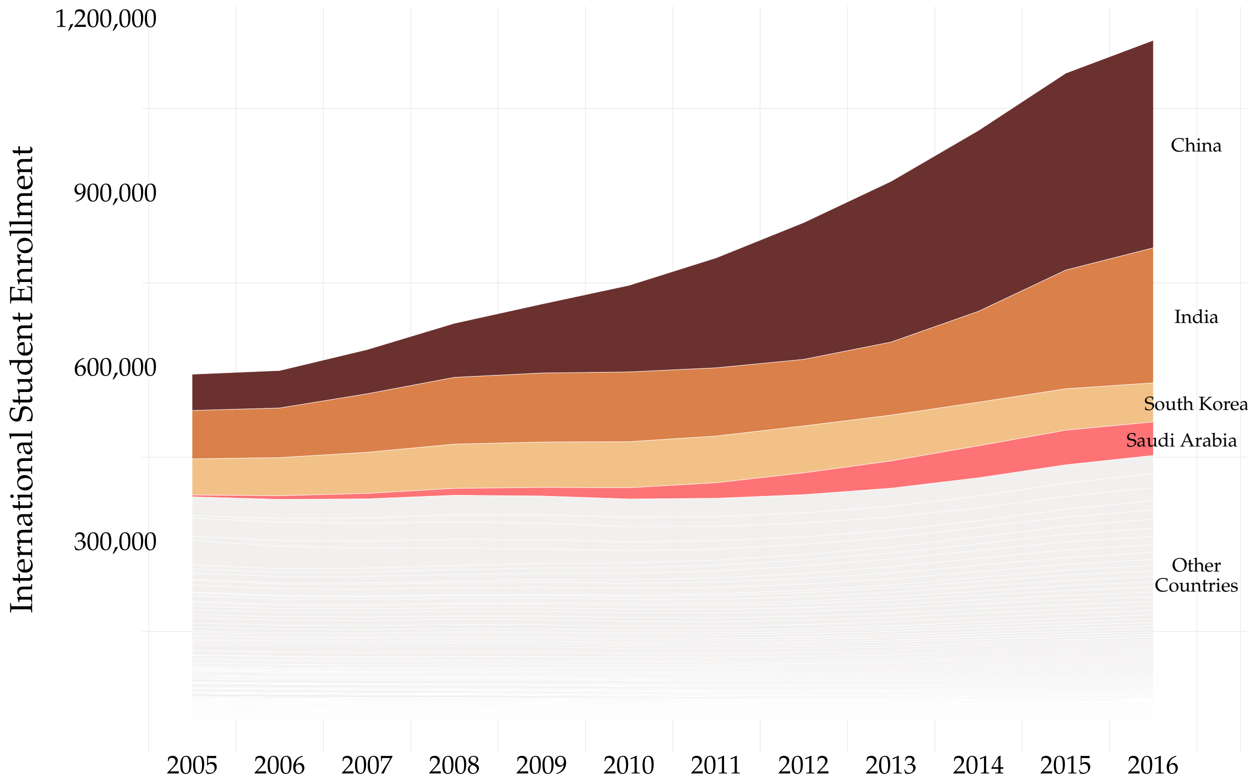
Notes: First stage results of price and rent regressions using the national-shift share instrument (1)-(4) and the country-of-origin instrument for prices (5) and (6). Values in () are standard errors clustered at the state level, and controls are the same as in Table (II). We report the Montiel Olea and Pflueger (2013) effective F-statistic (critical value at $\alpha = 0.05$ is ≈ 37).
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

TABLE F.4

OBSERVABLE CHARACTERISTICS: TOP AND BOTTOM COLLEGE TOWNS

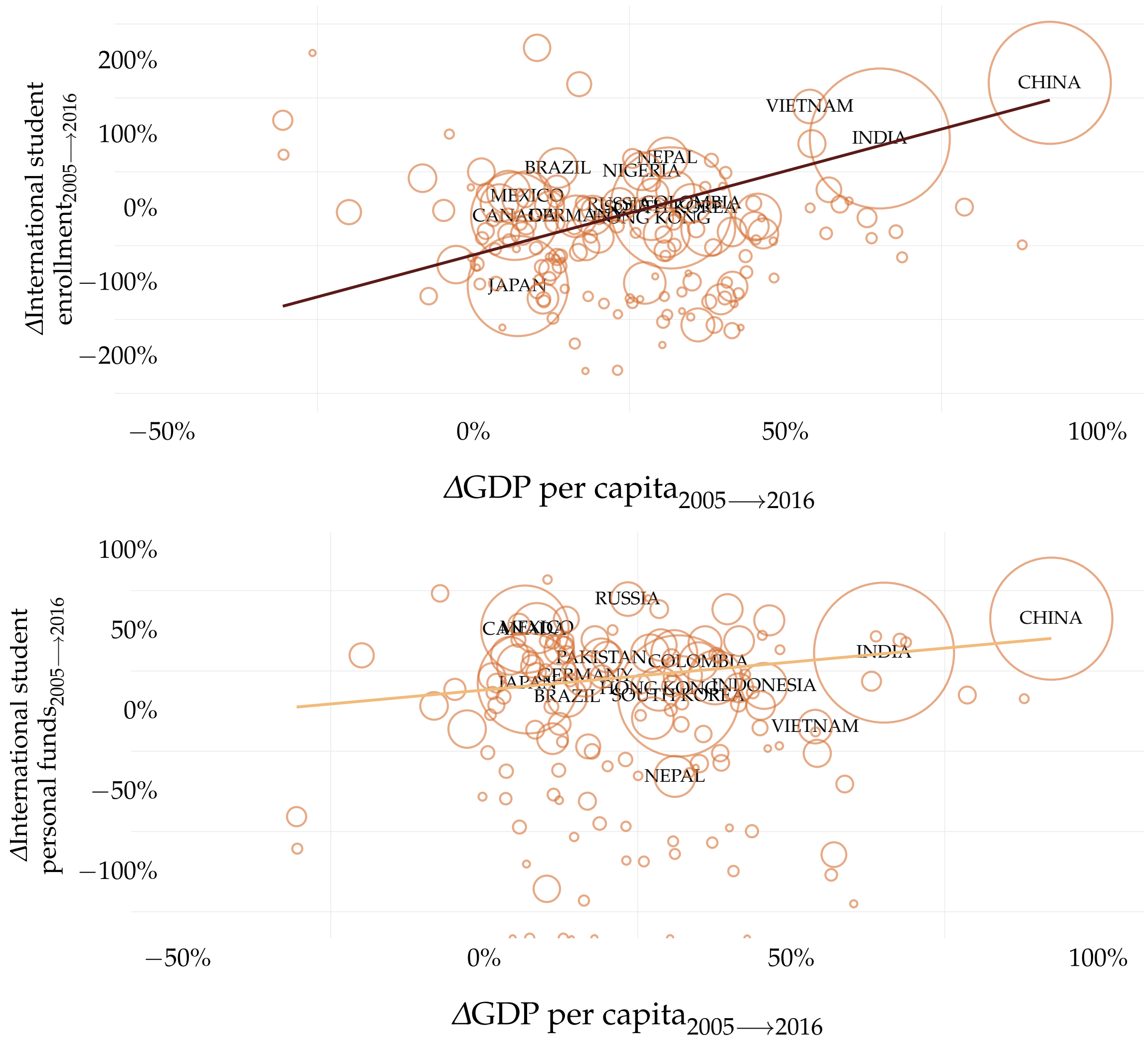
	College towns (Top decile)			College towns (Bottom decile)		
	1996-2001	2001-2005	2006-2016	1996-2001	2001-2005	2006-2016
Income growth	18%	14%	28%	18%	13%	21%
Population growth	23%	3%	13%	17%	4%	3%
Unemployment change (p.p.)	0.9	0.4	0.3	−0.7	0.4	0.5
Cum. int. inflow over total	16%	9%	32%	6%	4%	13%

Notes: Evolution of selected characteristics of top-performing and worst-performing college towns. We first rank college towns according to annualized price growth rates between 2005 and 2016, and then select top and bottom deciles. Top decile: College Station, TX, Grand Forks, ND, Weatherford, OK, Sioux Center, IA, Fargo, ND, Lake Charles, LA, Thibodaux, LA, Huntsville, TX, Denton, TX, State College, PA, Provo, UT, Grambling, LA, Fairfield, IA, Corvallis, OR, Orem, UT, Lewisburg, PA, Ruston, LA, Kearney, NE, Vermillion, SD, Moorhead, MN, Murray, KY, Princeton, NJ, Natchitoches, LA, Ithaca, NY. Bottom decile: Bradenton, FL, Big Rapids, MI, Bowling Green, OH, Oberlin, OH, Salisbury, MD, Daytona Beach, FL, Fort Myers, FL, Dayton, OH, Cocoa, FL, Winchester, VA, DeLand, FL, Ocala, FL, Worcester, MA, Ypsilanti, MI, Turlock, CA, West Haven, CT, Fort Pierce, FL, Seaside, CA, York, PA, Poughkeepsie, NY, University Park, IL, East Stroudsburg, PA, New London, CT, Flint, MI.



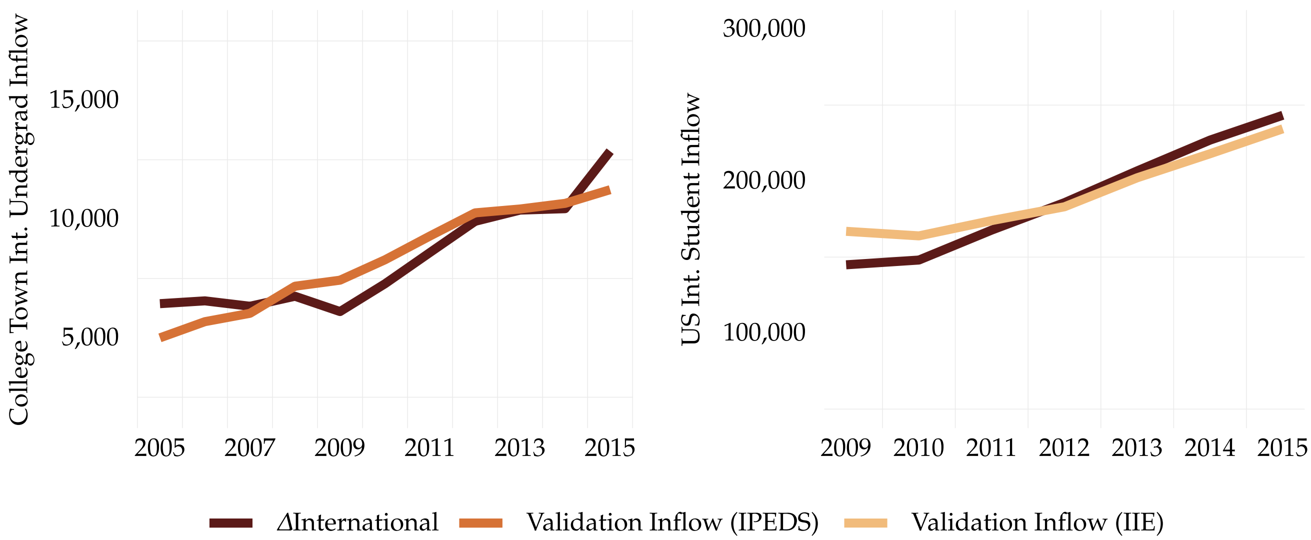
Notes: This figure plots international enrollment counts by country of origin in US universities from 2005 to 2016. Countries highlighted are the top-4 sending nations. Data come from administrative records obtained from the U.S. Immigration and Custom Enforcement (ICE), from the Department of Homeland Security (DHS).

FIGURE F.1
INTERNATIONAL ENROLLMENT IN THE US BY COUNTRY OF ORIGIN



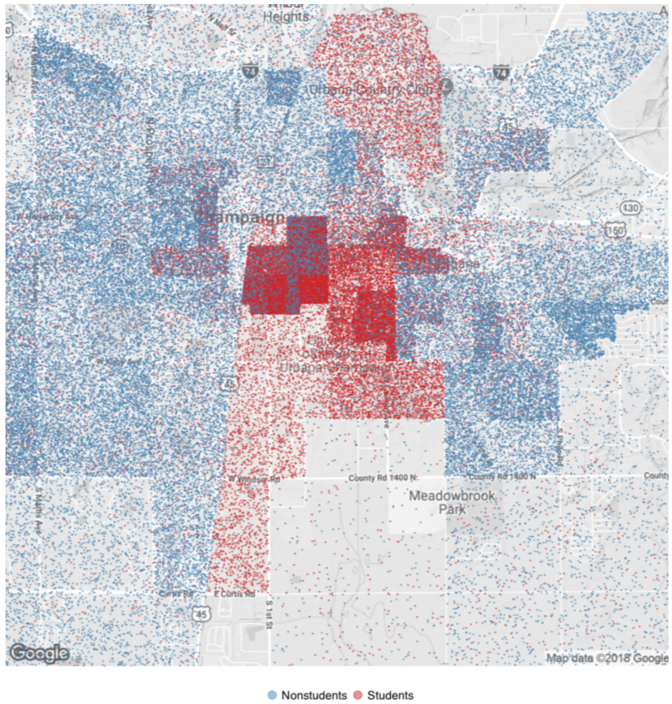
Notes: The top scatterplot compares country-level GDP growth per capita with international students from that country attending US universities during 2005 and 2016. The second figure compares GDP growth per capita to the amount students report to immigration officers upon entry in the US. Data come from administrative records obtained from the U.S. Immigration and Custom Enforcement (ICE), from the Department of Homeland Security (DHS). Circles represent enrollment counts.

FIGURE F.2
RELATIONSHIP BETWEEN ECONOMIC GROWTH, INTERNATIONAL STUDENT ENROLLMENT AND FUNDS



Notes: The first figure compares a version of our derived international student inflow ΔInternational for first-time degree-seeking freshmen undergraduate international students in college towns to IPEDS new enrollment of the same subgroup of students. The second figure uses our method to all degree-seeking undergraduate and graduate international students enrolled in the US to compare its accuracy with actual new international enrollment available from the IIE.

FIGURE F.3
VALIDATING THE INTERNATIONAL STUDENT INFLOW MEASURE



Notes: The figure displays student and nonstudent population counts by census block group using the ACS 2012-2016 5% sample. The student population is defined as individuals attending college, graduate or professional school. We randomly assign individuals within their census block group for visualization purposes. Each dot represents one person.

FIGURE F.4
STUDENT SEGREGATION IN CHAMPAIGN-URBANA, IL

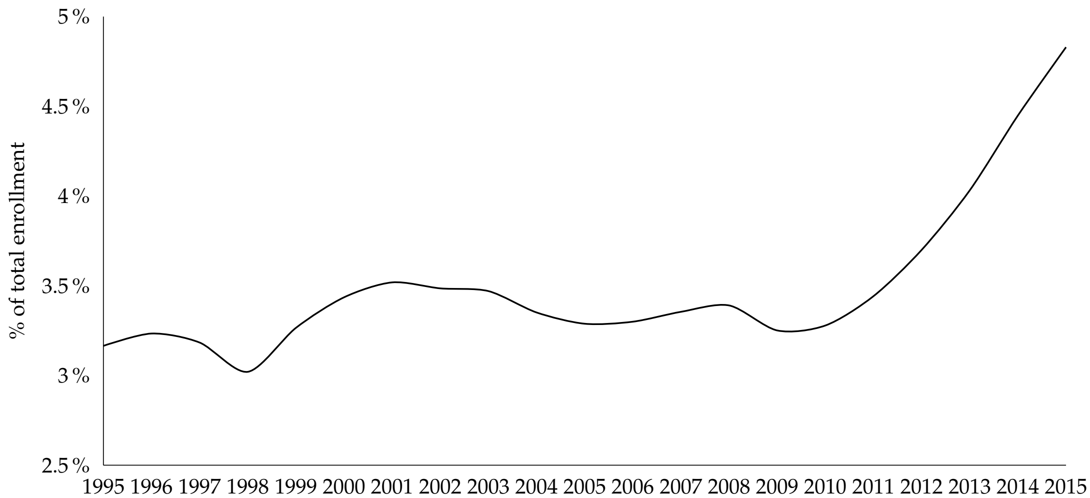


FIGURE F.5

SHARE OF INTERNATIONAL INTERNATIONAL ENROLLMENT US HIGHER EDUCATION

Notes: Includes degree-seeking full and part-time students in 4-year universities.

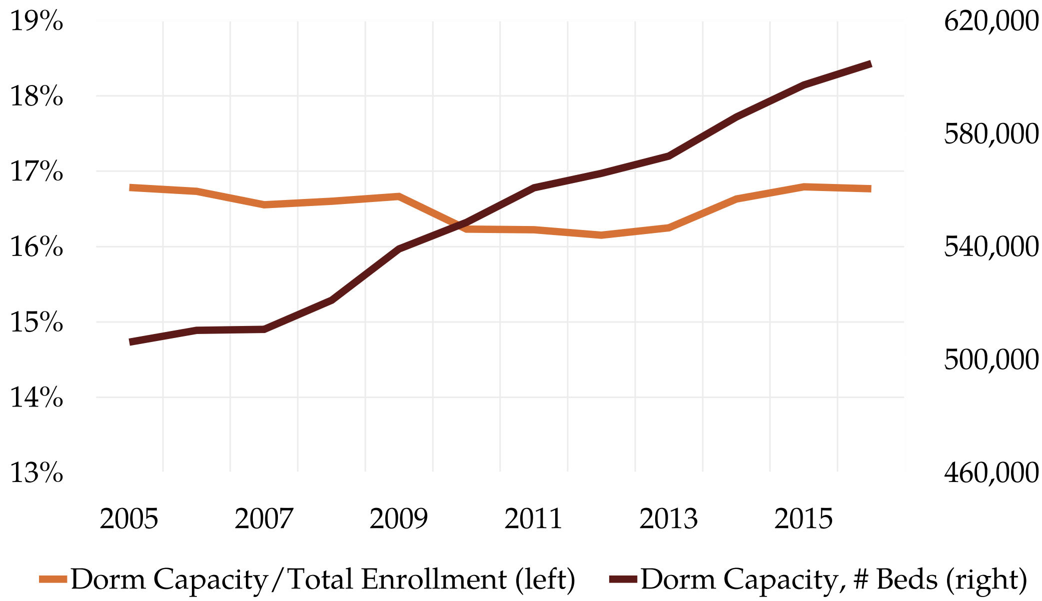


FIGURE F.6
DORM CAPACITY EXPANSION IN COLLEGE TOWNS

Notes: This figure shows the average share of enrollment that dorm capacity in a college town can absorb (on the left) and the total number of beds in college towns over time (on the right).