Supplementary Materials
Online Appendix

Neighborhood Identification Strategy

This section discusses our approach to identifying four-year colleges within commuting distance from community colleges. As just depicted, the first step in this identification framework consisted of selecting the measures that realistically capture commuting distances between two- and four-year colleges, depending on whether they are located in rural or nonrural zones. As further described below, the geocoded institutional information was retrieved from the U.S. Department of Education, Integrated Postsecondary Education Data System (2020b). However, due to some inconsistencies, wherein some institutions located in the same city or county were classified with diverging locale levels, the rural area classification was obtained from a neutral source: the U.S. Department of Agriculture Economic Research Service (USDAERS) under its most recent classification scheme of Rural-Urban Continuum Codes (USDAERS, 2020). USDAERS defines rural areas as having a population of up to 19,999 that is not adjacent to a metro area, wherein a metro area was required to have a minimum of 250,000 inhabitants.

Matrix Manipulation Procedures. From the description of Figure 3, note that no community colleges were allowed to be “neighbors” with other community colleges. This criterion is necessary because the main purpose of the identification is to test for the effect of affordability as a function of attending community colleges located within commuting distance of four-year institutions, not about the effect of community colleges having two-year neighbors; having said this, the influence of two-year neighbors is discussed in the methods section. Similarly, four-year institutions were not allowed to establish connections with other four-year neighbors.

Given these operationalization rules, the identification process consisted of first establishing the connections among all institutional types and levels (two, and four-year public, private non-for-profit, and private for-profit), as implemented in standalone packages (see Bivand et al., 2013) and, in our case, relying on the 20- and 40-mile radii criteria just described. Implementing these standard procedures implies that all institutions located within the radii-based criteria will be identified as neighbors. In matrix form, all institutions are represented in both the rows and columns of this matrix with the rows "identifying" connections with institutions in the columns. Every nonzero value in an intersecting row and column cell indicates that these institutions are neighbors, and such a value is typically the ratio of 1 over the total number of connections or neighbors the institution in the rows has in the region.[10] More specifically, if a given institution has two neighbors, the nonzero cells that intersect this institution's row with its neighboring institutions in the columns will both fall within a given threshold distance, and these cells will each have a value of 0.5 (or the result of the ratio $\frac{1}{2}$, where 2 is the number of neighbors for the institutions in this particular row). Similarly, if the number of neighbors for a given institution in the rows is 4, the corresponding intersecting cell value is 0.25 (or $\frac{1}{4}$). If an institution has only one neighbor, this value is 1 (or $\frac{1}{1}$).

Although the default process implemented in R Core Team (2020) renders a list object (Bivand et al., 2013), this object can be transformed to its corresponding matrix form just described. This transformation is represented in the following array of matrices under the panel "A. Original Output."

	A. Original Output					**B. First Trimming**				
	CC$_1$	**PUB**	**PRIV**	**PROF**	**CC$_2$**	**CC$_1$**	**PUB**	**PRIV**	**PROF**	**CC$_2$**
CC$_1$	0	0.25	0.25	0.25	0.25	0	0.25	0.25	0.25	0
PUB	0.5	0	0.5	0	0	0	0	0	0	0
PRIV	0.33	0.33	0	0	0.33	0	0	0	0	0
PROF	1	0	0	0	0	0	0	0	0	0
CC$_2$	0.5	0	0	0.5	0	0	0	0	0.5	0

	C. First Transformation					**D. Last Transformation**				
CC$_1$	0	1	1	1	0	0	0.33	0.33	0.33	0
PUB	0	0	0	0	0	0	0	0	0	0
PRIV	0	0	0	0	0	0	0	0	0	0
PROF	0	0	0	0	0	0	0	0	0	0
CC$_2$	0	0	0	1	0	0	0	0	1	0

In panel A note that we have the same institutions in the rows and columns. In this representation CC stands for community colleges, PUB for public, PRIV for not-for-profit, and PROF refers to for-profit institutions. We used subscripts to identify different institutions of the same type (e.g.,

CC_1 and CC_2). As standard, the diagonal is a vector of zeros since no institution is allowed to self-select itself. The off-diagonal captures all institutions that meet (or do not meet) the distance threshold criterion. For example, consider the first row, CC_1. Note that four institutions are located within the distance threshold of this community college. Following row-standardization procedures, the weights are $\frac{1}{4}$, or 0.25, as just discussed. In this default output, note also that the public four-year institution also has two neighbors (a community college (CC_1) and a not-for-profit institution), which violates our identification rules (four-year selecting CCs and other four-year colleges). Similarly, the not-for-profit college has three neighbors, and the for-profit college neighbors CC_1 (also violating our rules). Finally, note that CC_2 also neighbors both CC_1 and the for-profit institution (each cell with initial values of 0.5 and indicate more identification violations).

To capture the connections of interest, as depicted in Figure 3, this matrix needed to be trimmed (i.e., some connections needed to be removed). Specifically, as shown in the panel "B. First Trimming" all nonzero connections coming from the rows to the columns that included (a) non-community colleges and (b) community colleges selecting other community colleges needed to become zero. This transformation is shown in red font in Panel B. For example, the selections involving CC_1 and CC_2, which had values of 0.25 and 0.5 in the first and last rows, respectively, were changed to zero.

The next transformation required that all valid nonzero cells, as reflected in panel C, were transformed to 1. This transformation enabled us to apply a sum of rows function to count the number of neighbors that each community college had in this network. Specifically, CC_1 ended up with three neighbors and CC_2 with one neighbor. Finally, the transformation reflected in panel D once more followed the row-standardization procedures, which allowed us to capture institutional heterogeneity as follows. Once all valid neighbors (as represented in Figure 3) were identified, we were able to add attributes to these neighbors such as research intensity, open-door status, and the net price charged the previous academic year. With these attributes we were able to obtain spatially lagged indicators that represent the average values of those neighbors on a given

attribute of interest. For example, assume that CC_1's neighbors charged \$12,000 (public), \$21,000 (private not-for-profit), and \$18,000 (for profit). The lagged indicators are the result of multiplying these attributes by the row-standardized weights and adding them together to obtain the mean value, which in this case is
$(12,000 * 0.33) + (21,000 * 0.33) + (18,000 * 0.33) = \$16,830$. These weights can also be applied to binary indicators, such as being classified as research university (1 if true, 0 otherwise), wherein the mean would reflect the proportion of neighbors meeting this classification.

To obtain mean values separately by sector (see Neighbor Heterogeneity section in Table 1), instead of including all four institution types in the same identification depicted in our matrices array, we included one four-year sector at a time, which required us to execute the specifications described three times. Additionally, we repeated these procedures by rural and nonrural areas.[11]

The empirical results obtained from these identification processes can be observed in Figures 4 and 5, which, for clarity purposes, separate the depictions by rural (Figure 4) and nonrural areas (Figure 5). A total of 939 community colleges are represented in those maps with 847 community colleges in nonrural areas and 92 in rural zones. The color schemes follow the depiction in Figure 3. The original input as obtained from IPEDS included 2,246 four-year institutions, of which 2,147 were located in nonrural areas and 99 in rural zones.[12]

As an example of the identification of heterogeneous neighboring structures, we briefly discuss Figure 6(a), which depicts a community college located in a rural area. This community college has five four-year neighbors, three not-for-profit (gray), one for-profit (red), and one public (cyan) institution. In going back to the notion of heterogeneity, for this institution, 60% of its neighbors are not-for-profit colleges, 20% are public, and 20% are for-profit colleges. Similarly, Figure 6(b) depicts a community college located in a nonrural area. In this case, this community college has seven four-year neighbors: one public, one private for-profit, and five not-for-profit colleges. Note that in both cases none of the four-year institutions were connected among themselves. A further analysis of these maps relying on their HTML versions (available here https://cutt.ly/UjNSBNw and here https://cutt.ly/qjNS0lT), corroborated that no community colleges were identified as neighbors with other community colleges. To close this section, note that although in some instances neighbors were detected among institutions located in different states, sensitivity checks that removed these institutions from our model specifications did not affect the results discussed in this study (this may be a byproduct of tuition reciprocity agreements, as discussed by González Canché (2014)).

Table A1

Net Price and Tuition Revenue per FTE SAR models

Panel A: net_price_i and Net Tuition Models

	Dependent variable: net_price_i				Dependent variable: net_tuition_i			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
neighbor? (0,1)	−460.168*				−8.375			
	(267.602)				(97.522)			
#neighbors		7.874				−5.432**		
		(6.739)				(2.524)		
neigh_public? (0,1)			−194.135				−23.742	
			(226.379)				(81.827)	
neigh_private? (0,1)			−275.697				−78.824	
			(228.207)				(82.471)	
neigh_profit? (0,1)			−202.789				−178.029**	
			(204.714)				(74.071)	
number_public_i				38.597				−0.977
				(61.577)				(22.639)
number_private_i				−5.124				0.044
				(16.873)				(6.183)
number_profit_i				26.170				−30.219**
				(32.463)				(12.112)
non_resident_alien_i					7,813.945***	8,217.099***	7,787.832***	8,162.246***
					(1,603.665)	(1,609.243)	(1,597.521)	(1,615.759)
prop_part_time_i	484.487	471.336	481.638	431.767	521.248**	446.619*	549.664**	490.861*
	(682.296)	(687.263)	(683.495)	(689.725)	(251.775)	(251.855)	(251.058)	(252.045)

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Table A1 – continued from previous page

	Dependent variable: net_price_i				Dependent variable: net_tuition_i			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
prop_loan_i	5,156.445***	5,075.605***	5,140.407***	5,000.837***	2,195.708***	2,160.451***	2,195.321***	2,198.197***
	(805.485)	(803.955)	(812.661)	(807.909)	(293.461)	(291.974)	(295.078)	(292.341)
pct_living_on_campus_i	2,123.229**	2,630.659***	2,078.077**	2,620.552***	−386.422	−483.889	−536.063	−454.283
	(922.152)	(908.500)	(923.235)	(910.021)	(330.702)	(324.241)	(330.628)	(324.121)
transf_rate_FTE_i	1,211.422	1,252.272	1,423.977	1,205.314	1,924.330***	1,994.542***	2,008.499***	2,030.978***
	(1,037.790)	(1,039.274)	(1,037.270)	(1,039.967)	(376.358)	(375.576)	(375.115)	(375.066)
Black_i	2,180.719**	1,843.608*	2,330.182**	1,919.543*	−2,105.014***	−1,900.893***	−2,011.955***	−1,948.290***
	(956.719)	(994.424)	(960.658)	(996.984)	(351.184)	(362.762)	(350.971)	(362.662)
Hispanic_i	−1,749.708*	−1,999.029**	−1,785.904*	−1,921.180**	−2,139.852***	−2,029.135***	−2,094.420***	−2,035.054***
	(912.820)	(924.240)	(913.420)	(931.685)	(332.843)	(335.402)	(331.536)	(337.355)
Asian_i	−1,940.624	−1,949.244	−1,655.667	−1,607.656	−2,387.176***	−2,390.320***	−2,201.881***	−2,600.725***
	(2,057.879)	(2,060.341)	(2,065.926)	(2,090.910)	(767.563)	(765.134)	(767.495)	(774.480)
race_other_i	2,170.643	1,848.629	2,236.154	1,861.577	−945.984	−818.538	−868.272	−841.598
	(1,626.757)	(1,645.684)	(1,626.971)	(1,648.308)	(579.700)	(580.877)	(577.640)	(579.594)
Northeast	−966.591**	−1,124.345***	−955.451**	−951.273**	472.961***	527.483***	503.318***	396.783**
	(395.907)	(400.482)	(396.923)	(442.809)	(147.857)	(148.541)	(146.797)	(162.938)

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Table A1 – continued from previous page

	Dependent variable: net_price_i				Dependent variable: net_tuition_i			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Midwest	−1,008.771***	−1,037.428***	−1,001.742***	−924.867**	−10.036	6.560	−0.853	−68.283
	(351.042)	(352.512)	(353.478)	(372.309)	(130.991)	(130.670)	(130.706)	(136.973)
South	−834.654***	−794.298**	−943.882***	−735.736**	273.768**	236.263*	217.050*	196.633
	(316.658)	(319.904)	(325.471)	(325.842)	(120.703)	(121.359)	(122.428)	(123.318)
Rural_i	172.002	250.010	110.394	273.476				
	(375.959)	(375.028)	(378.383)	(375.767)				
prop_EITC_z	1,474.070	1,750.223	1,240.466	1,947.528	−785.884	−662.942	−1,086.491*	−828.683
	(1,695.047)	(1,683.856)	(1,704.561)	(1,697.855)	(657.075)	(647.766)	(654.757)	(651.046)
Gini_z	−47.219	−378.298	110.262	−362.359	−2,345.435***	−2,073.825***	−2,251.623***	−2,102.709***
	(1,683.257)	(1,718.637)	(1,690.121)	(1,718.451)	(704.661)	(712.661)	(703.182)	(712.994)
med_income_z	0.013	0.013	0.013	0.014	0.008*	0.009*	0.009*	0.008*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.005)	(0.005)	(0.005)	(0.005)
med_rent_z	−0.370	−0.415	−0.358	−0.410	−0.138	−0.110	−0.152	−0.120
	(0.473)	(0.475)	(0.473)	(0.475)	(0.179)	(0.179)	(0.179)	(0.179)
rent_income_ratio_z					1,545.478***	1,515.791***	1,617.145***	1,526.031***

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Table A1 – continued from previous page

	Dependent variable: net_price_i				Dependent variable: net_tuition_i			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
					(488.167)	(483.870)	(483.526)	(482.777)
single_mother_hshld_z					−507.637*	−531.887*	−498.418*	−477.663
					(301.995)	(300.983)	(300.734)	(302.065)
citzn_born_abroad_z	1,536.566	551.766	2,012.974	623.179	570.371	1,153.029	857.719	1,218.656
	(2,333.155)	(2,456.872)	(2,347.406)	(2,465.357)	(857.407)	(896.288)	(859.240)	(897.847)
prop_crime_z	2,354.696	2,394.808	2,343.095	2,560.914	−612.738	−244.670	−805.884	−361.688
	(4,736.503)	(4,754.921)	(4,728.571)	(4,756.196)	(1,729.623)	(1,729.623)	(1,720.239)	(1,726.146)
Black_z	−1,338.688	−1,480.333*	−1,107.194	−1,578.730*	780.480**	741.689**	967.031***	766.921**
	(880.300)	(874.536)	(895.614)	(880.493)	(335.962)	(333.262)	(339.567)	(332.969)
Hispanic_z	−407.677	−409.430	−250.529	−536.138	767.147**	737.839**	862.655**	779.198**
	(967.973)	(969.055)	(975.578)	(980.173)	(345.003)	(344.350)	(346.314)	(346.593)
Asian_z	711.626	892.724	625.828	632.981	426.645	313.220	390.375	488.285
	(1,496.201)	(1,504.757)	(1,496.357)	(1,529.620)	(545.120)	(546.319)	(543.303)	(554.557)
race_other_z	1,261.690	1,210.682	1,373.382	1,066.154				
	(2,123.283)	(2,124.643)	(2,124.551)	(2,129.596)				

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Table A1 – continued from previous page

	Dependent variable: net_price_i				Dependent variable: net_tuition_i			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
prop_adlts_up_HS_c	5,332.964***	5,438.644***	5,377.020***	5,405.583***	680.505	839.187	599.824	869.520
	(1,492.571)	(1,494.269)	(1,493.592)	(1,494.203)	(540.437)	(539.423)	(538.885)	(538.266)
unemplymnt_rate_c	−3,116.268	648.815	−5,448.282	893.510	4,347.479	3,313.013	2,422.510	3,081.165
	(8,475.399)	(8,507.769)	(8,656.956)	(8,510.141)	(3,084.809)	(3,088.158)	(3,133.597)	(3,082.309)
prop_poverty_c	−12,758.250***	−13,114.140***	−12,972.170***	−12,863.370***	−5,795.311***	−5,873.965***	−5,784.031***	−6,117.331***
	(2,871.771)	(2,863.021)	(2,894.072)	(2,879.636)	(1,048.198)	(1,040.475)	(1,050.929)	(1,043.924)
death_rate_c	−18,702.740***	−16,980.550***	−19,260.690***	−16,852.910***	−1,191.527	−1,470.374	−1,951.372	−1,634.445
	(6,097.577)	(6,072.624)	(6,116.527)	(6,071.564)	(2,199.661)	(2,179.416)	(2,200.905)	(2,175.479)
prop_net_migration_c	1,113.399	1,152.783	819.367	1,306.794	−2,149.394***	−2,235.768***	−2,280.316***	−2,384.789***
	(1,174.140)	(1,179.465)	(1,192.151)	(1,195.306)	(426.485)	(426.768)	(431.076)	(431.340)
State.Gross.Domestic.Product_s	71.640***	70.491***	68.367***	71.860***	23.356***	23.369***	22.138***	22.459***
	(14.764)	(14.767)	(14.794)	(14.831)	(5.421)	(5.399)	(5.403)	(5.417)
Absolute.Domestic.Migration_s	27.097***	27.501***	27.476***	28.132***	−4.662	−4.314	−4.445	−4.589
	(9.715)	(9.724)	(9.753)	(9.742)	(3.578)	(3.566)	(3.569)	(3.563)
Non.Farm.Payroll_s	−115.804***	−114.507***	−111.458***	−116.420***	−23.068***	−23.288***	−21.586***	−22.553***
	(18.717)	(18.730)	(18.765)	(18.871)	(6.840)	(6.817)	(6.823)	(6.857)

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Table A1 – continued from previous page

	Dependent variable: net_price_i				Dependent variable: net_tuition_i			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
state_sup_per_inhabi_s	−5.401***	−5.103***	−5.519***	−5.024***	−4.852***	−4.922***	−5.003***	−5.004***
	(1.365)	(1.366)	(1.369)	(1.368)	(0.503)	(0.500)	(0.501)	(0.500)
Need_based_s	2.346***	2.314***	2.321***	2.323***	−0.949***	−0.928***	−0.935***	−0.917***
	(0.691)	(0.693)	(0.694)	(0.693)	(0.255)	(0.255)	(0.255)	(0.254)
Nonneed_based_s	−1.177**	−1.263**	−1.143**	−1.281**	0.618***	0.628***	0.668***	0.648***
	(0.571)	(0.570)	(0.573)	(0.570)	(0.211)	(0.210)	(0.210)	(0.209)
Nongrant_Aid_s	3.396***	3.340***	3.469***	3.337***	3.432***	3.465***	3.495***	3.491***
	(1.131)	(1.133)	(1.132)	(1.132)	(0.417)	(0.416)	(0.415)	(0.415)
Constant	9,591.122***	9,147.275***	9,610.216***	8,957.443***	4,935.109***	4,742.297***	5,164.924***	4,895.877***
	(1,549.839)	(1,511.728)	(1,535.797)	(1,525.620)	(568.206)	(552.419)	(560.954)	(557.000)
AIC	17,785.420	17,787.000	17,787.890	17,790.130	15,882.220	15,877.620	15,877.970	15,876.990
Log Likelihood	−8,854.708	−8,855.500	−8,853.943	−8,855.064	−7,902.109	−7,899.809	−7,897.984	−7,897.495
Lambda	0.009	0.09	0.009	0.09	0.018	0.018	0.017	0.017
Moran's I SAR $\epsilon_i^{\dagger}$	-0.008	-0.007	-0.09	-0.006	0.024	0.023	0.023	0.022

Num. obs. = 939, †Model residuals as depicted in equation (2), SE in parentheses, *p<0.1; **p<0.05; ***p<0.01

All control variables are shown in Table 1 and model selection is depicted in Figure 8 per outcome of interest

Table A2
Neighbor Heterogeneity SAR models

	Net Price	Net Tuition
	(1)	(2)
number_neighbors	18.162**	−0.084
	(8.259)	(2.981)
neigh_public? (0,1)	−1,243.339**	−698.935***
	(537.277)	(191.064)
neigh_private? (0,1)	−1,542.742**	−242.170
	(606.618)	(217.968)
neigh_profit? (0,1)_i	259.739	−148.926
	(658.111)	(235.428)
lag.net_price_public_i	0.072**	0.042***
	(0.032)	(0.011)
lag.net_price_private_i	0.059**	0.003
	(0.024)	(0.009)
lag.net_price_profit_i	−0.034	0.003
	(0.027)	(0.010)
prop neigh Research	576.422	40.855
	(585.509)	(209.461)
prop neigh Open Door	524.129	−300.419*
	(506.232)	(182.128)
non_resident_alien_i		8,448.060***
		(1,875.351)
prop_part_time_i	−402.933	309.418
	(856.225)	(309.510)
prop_loan_i	4,251.446***	1,948.260***
	(961.720)	(345.543)
pct_living_on_campus_i	1,318.130	−1,050.242**
	(1,443.815)	(513.288)
transf_rate_FTE_i	1,048.449	2,159.510***
	(1,346.535)	(482.636)
Black_i	2,321.176**	−2,071.714***

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Table A2 – continued from previous page

	Net Price	Net Tuition
	(1)	(2)
	(1,147.368)	(413.656)
Hispanic_i	−2,794.738**	−1,990.816***
	(1,109.787)	(398.292)
Asian_i	−1,366.647	−1,908.607**
	(2,296.292)	(839.441)
race_other_i	3,502.499	−1,191.356
	(2,238.336)	(843.124)
Northeast	−1,202.001**	319.439*
	(481.765)	(171.545)
Midwest	−1,139.785**	−12.267
	(450.476)	(160.594)
South	−971.580**	296.901**
	(411.350)	(150.642)
Rural_i	−542.697	
	(560.123)	
prop_EITC_z	1,657.371	−1,223.051
	(1,961.420)	(761.423)
Gini_z	−1,283.705	−2,350.405***
	(1,954.706)	(805.671)
med_income_z	0.020	0.009*
	(0.014)	(0.005)
med_rent_z	−0.847	−0.251
	(0.530)	(0.201)

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Table A2 – continued from previous page

	Net Price	Net Tuition
	(1)	(2)
rent_income_ratio_z		1,999.957***
		(569.831)
single_mother_hshld_z		−435.674
		(339.386)
citzn_born_abroad_z	−1,016.258	724.623
	(2,743.167)	(993.465)
prop_crime_z	−3,101.664	−2,573.142
	(6,091.232)	(2,174.990)
Black_z	−760.634	891.196**
	(1,027.710)	(387.219)
Hispanic_z	563.117	822.230**
	(1,127.675)	(399.327)
Asian_z	1,683.830	652.726
	(1,637.741)	(592.916)
race_other_z	3,536.686	
	(2,496.095)	
prop_adlts_up_HS_c	7,544.145***	1,392.229**
	(1,872.639)	(672.415)
unemplymnt_rate_c	−28,333.060*	6,791.204
	(15,142.320)	(5,378.567)
prop_poverty_c	−13,676.050***	−6,248.923***
	(3,629.938)	(1,307.332)
death_rate_c	−28,929.140***	−3,423.854
	(8,026.936)	(2,882.093)

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Table A2 – continued from previous page

	Net Price	Net Tuition
	(1)	(2)
prop_net_migration_c	−866.507	−1,971.128***
	(1,552.988)	(553.935)
State.Gross.Domestic.Product_s	56.225***	24.358***
	(17.848)	(6.397)
Absolute.Domestic.Migration_s	25.940**	−10.597**
	(12.257)	(4.387)
Non.Farm.Payroll_s	−109.462***	−19.754**
	(22.747)	(8.137)
state_sup_per_inhabi_s	−4.811***	−6.105***
	(1.787)	(0.641)
Need_based_s	2.212***	−1.053***
	(0.807)	(0.291)
Nonneed_based_s	−1.426**	0.808***
	(0.669)	(0.242)
Nongrant_Aid_s	1.910	3.477***
	(1.296)	(0.467)
Constant	12,698.150***	5,692.808***
	(1,996.139)	(723.168)
AIC	11,795.800	10,522.790
Log Likelihood	−5,849.899	−5,212.395
Lambda	0.010	0.009
Moran's I SAR $\epsilon_i^{\dagger}$	-0.009	0.023

Num. obs. = 627, †Model residuals as depicted in equation (2)

SE in parentheses, *p<0.1; **p<0.05; ***p<0.01

All control variables are shown in Table 1 and model selection is depicted in Figure 8 per outcome of interest

†lag indicates the average price of neighboring in net price in 2017-2018.