Supplementary Material

Supplementary S1: scaling models for residential land sales under three pricing mechanisms

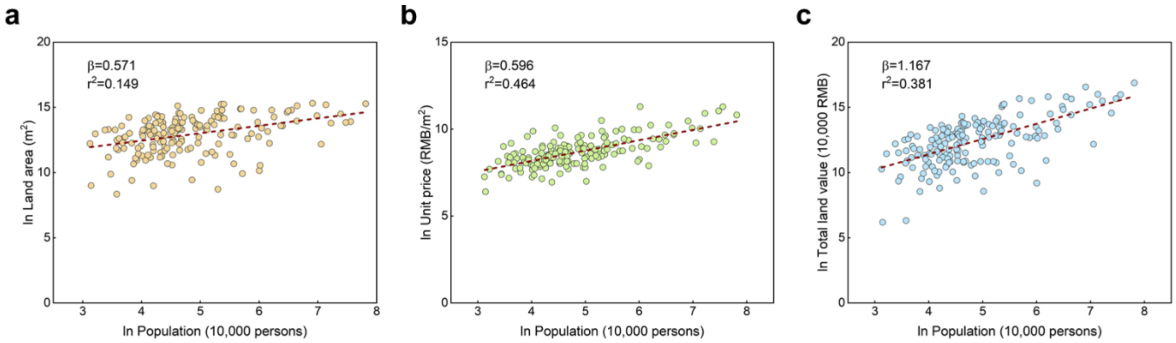


Figure S1: Scaling models for residential land sales (auction price) (2022): (a) land area, (b) unit price, (c) total land value.

Note (S1): We illustrate scaling models of land area, unit land price and total land-value for a single year, to make some basic points about our models and data. We argue (Methods) that land values expressed in the residential auction market are likely to be a relatively pure indicator of social surplus. Since total land-value equals land area times unit price, the power law beta coefficients for *area* and *unit price* in the log-log version of [1] sum to the beta coefficient of the *total land value* model. Of the three performance indicators in Figure S1, *unit price* has the best fit, revealing an expected consistency of higher prices in larger cities. *Area* has the poorest fit, indicating several complex dynamics, including local policy and governance, and some larger cities having below-trend land sales volume, likely due to growth limitations and different cities being at different points in local business cycles. *Unit price* rising with population likely reflecting a density effect, higher construction costs in larger cities, and compensation costs of removing existing collective villages and state-owned enterprise users. In China, compensating existing collectives is the main cost of land acquisition facing city governments in bringing forward new urban land for leasing, and these costs are a function of among other things, costs of relocation including compensation apartments and business premises. Unit price cannot be taken to measure social surplus, which is a volume rather than a rate. Land area *is* volumetric, but without value, so we need the two together. Land area rises sub-linearly, as predicted of urban infrastructure by urban scaling theory, the below pro-rata expansion interpreted as a scale-economy related to densification as cities increase in population, with any given unit (length or area) of infrastructure serving more people as cities densify.

Supplementary S2: Ranked scaling residuals

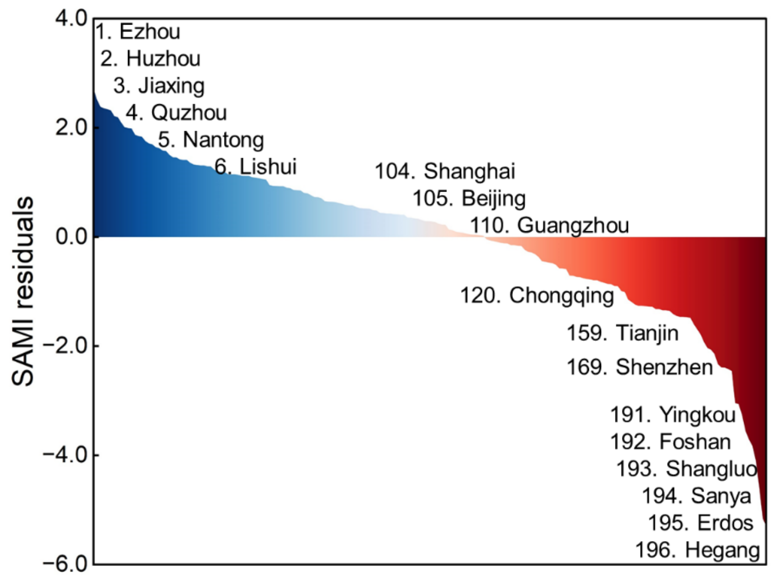


Figure S2: Ranked SAMI residuals around the 2018 trend-line, identifying, for illustration, the six highest negative residuals (191-196), six highest positive residuals (1-6), and 6 tier 1 cities and cities directly under control of central government (104-169).

Note (Figure S2): Chongqing, Tianjin and Shenzhen are prominent cities that illustrate a range of reasons for having a social surplus indicator *below* the population-adjusted system mean. Chongqing (30 million resident population) is a large mountainous city growing under the constraints of China's western periphery and with topographic constraints in creating new urban land. Tianjin, (14 million) a former treaty port city in Northern China, struggles under the shadow of the greater Beijing region. Shenzhen (18 million), over the border from Hong Kong and the fastest growing mega city in history, has simply run out of space. The same can be said of the positive outliers. Jiaxing, for example, birthplace of one of China's neolithic farming cultures, is located in one of China's traditionally wealthiest provinces (Zhijiang), adjacent to one of the country's wealthiest large cities (Huangzhou). Geography, path dependence, centrality, economic structure and governance, all have a bearing on the luck of the draw in determining a city's social surplus. We suggest, below, a method of scientifically adjusting a city-size tax base accordingly.

Table S2: SAMI residuals around the 2018 trend-line for cities with the 20 highest positive residuals (ranked 1-20), 20 highest negative residuals (ranked 177-196), and 6 tier 1 cities and cities directly under control of central government (ranked 104-169).

Cities with the 20 highest positive residuals			Cities with the 20 highest negative residuals			Tier 1 cities and cities directly under control of central government		
Rank	**City**	**Scaling residuals**	**Rank**	**City**	**Scaling residuals**	**Rank**	**City**	**Scaling residuals**
1	Ezhou	2.704	177	Tonghua	-1.783	104	Shanghai	0.137

2	Huzhou	2.513	178	Yinchuan	-1.931	105	Beijing	0.123
3	Jiaxing	2.385	179	Zhaoqing	-2.034	110	Guangzhou	0.050
4	Quzhou	2.358	180	Shaoguan	-2.065	120	Chongqing	-0.116
5	Nantong	2.342	181	Harbin	-2.138	159	Tianjin	-1.261
6	Lishui	2.320	182	Weihai	-2.329	169	Shenzhen	-1.409
7	Taizhou (Zhejiang)	2.214	183	Benxi	-2.387			
8	Zhangzhou	2.197	184	Guangyuan	-2.391			
9	Chuzhou	2.097	185	Anshan	-2.418			
10	Shangrao	2.012	186	Daqing	-2.453			
11	Shaoxing	1.995	187	Dalian	-3.043			
12	Zhoushan	1.989	188	Hohhot	-3.060			
13	Jinan	1.874	189	Jixi	-3.254			
14	Suzhou (Jiangsu)	1.850	190	Shuozhou	-3.554			
15	Jingdezhen	1.838	191	Yingkou	-3.705			
16	Heze	1.757	192	Foshan	-3.823			
17	Jinhua	1.717	193	Shangluo	-4.091			
18	Zhongshan	1.698	194	Sanya	-4.604			
19	Xuancheng	1.648	195	Ordos	-5.155			
20	Sanming	1.627	196	Hegang	-5.296			

Supplementary S3: Time series plots of total land for selected cities with negative and positive residuals in the 2018 scaling model.

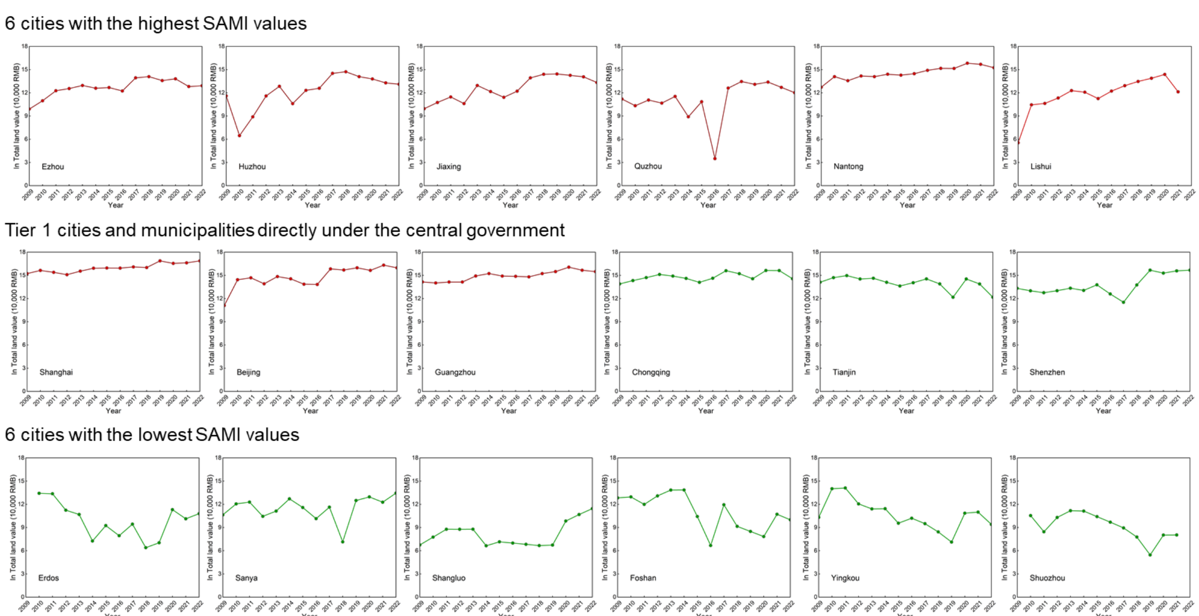


Figure S3: Time series plots of total land value (10,000 RMB, residential land, priced at auction) for selected cities that have negative and positive residuals in 2018 (and high and low performance in Figure S2).

Note (S3): The six cities with the highest positive standardized deviation from the trendline have all broadly experienced rising absolute social surplus over the period, with isolated dips and some indication of business cycle perturbation. These are cities in a rapid development stage. The 6 top tier cities, at a more mature stage of post-1979 mixed-market development have higher but flatter upward trends in social surplus, with the exception of Tianjin. The poorest performing 6 cities display a more chaotic movement on our social surplus indicator, with 4 of the 6 having an overall downward sloping trend. These are smaller and under-developed cities with immature land markets. We conclude that there is temporal stability in our unearned land value metric, warranting further exploration of its use as a base for a land value tax.

Supplementary S4: Movement of SAMI residuals over time for selected cities

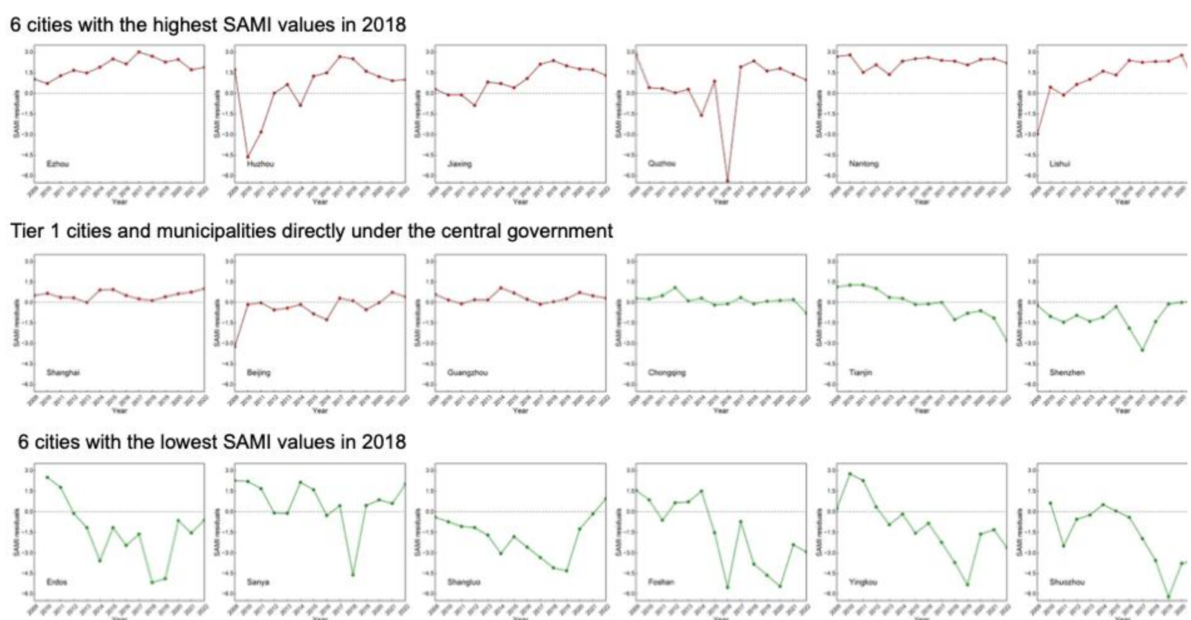


Figure S4(a): City plots of residuals around the scaling model lnTLV=a*b^lnPop, (for total value of new residential land priced by auction in 2018, in 10,000 RMB), for the 6 cities with the highest and lowest residuals in 2018.

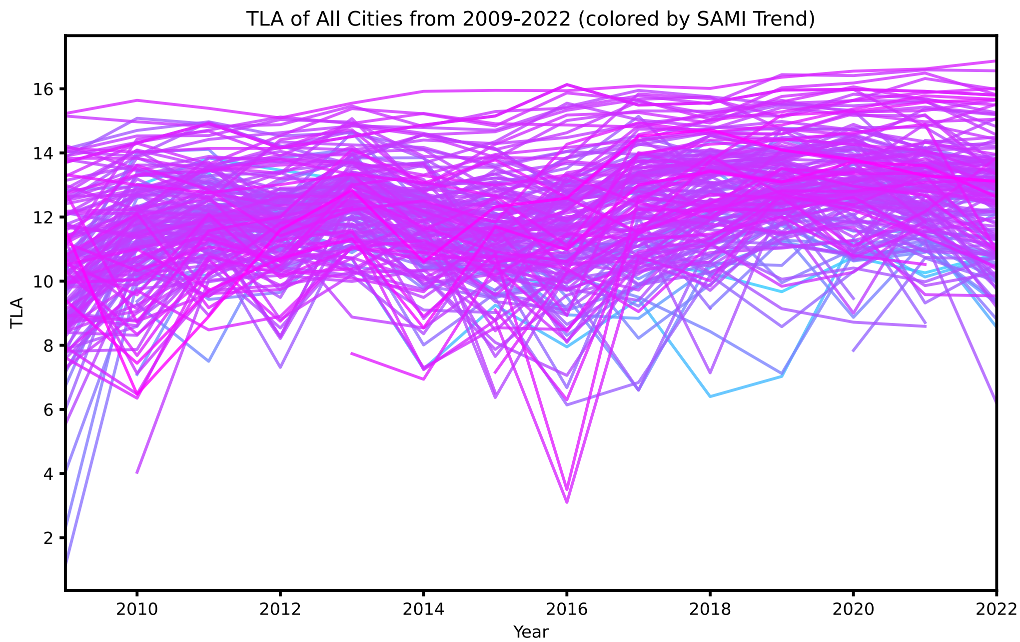


Figure S4(b) Scaling residual trends for all prefecture cities, over 14 years, showing predominance of upward trending performance in relation to the system mean.

Note (S4b): Colored by SAMI trend (blue: slope<0; red: slope>0). SAMI trend is calculated as the slope of regressing SAMI values on years.

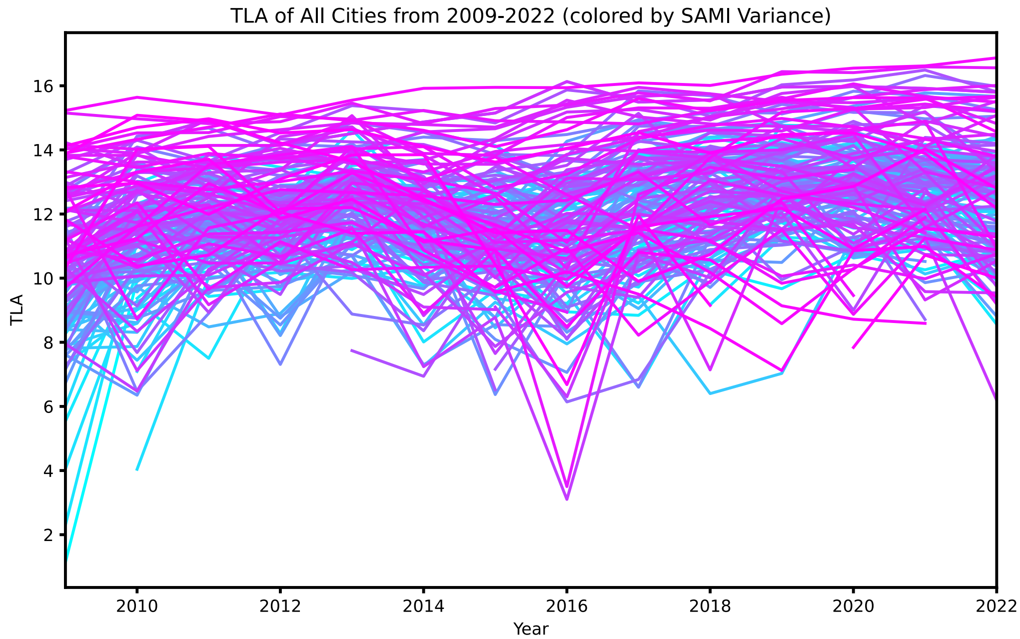
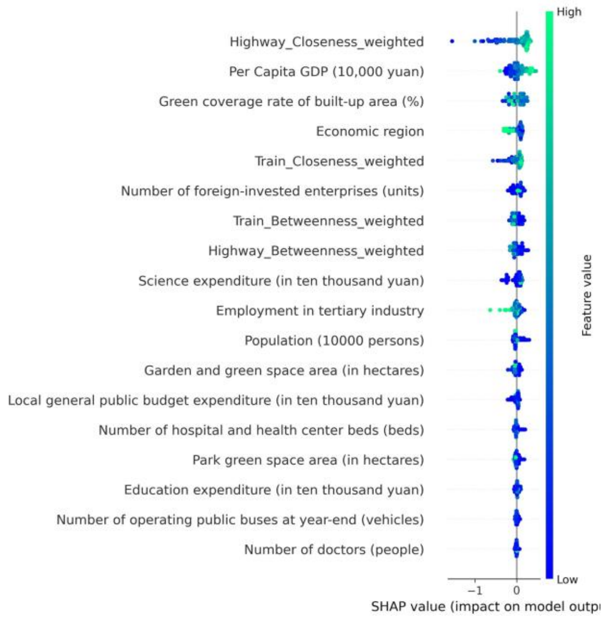


Figure S4(c). Trend lines regressing scaling residuals on year, for of all cities from 2009-2022 (colored by residuals' variance).

Note (S4c): Variance calculation is after detrending. Variance is colour coded (red-high, blue is low variance). The results reveal that cities starting the time series with lower SAMIs (negative deviations from the scaling trend line) – i.e. the lines starting at lower values on the y axis – tend to have lower variance (blue coloured) while better performing cities tend to have higher variance.

Supplementary S5: Modelling the explanation of scaling residuals

Note**:** Results of i) Random Forest (RF) Machine Learning model predicting residuals around a 2018 land value urban scaling model: ln(Total Residential Land Value created at auction) = ln(Constant)+ln(Population)*β, for Chinese prefecture cities; and ii) an equivalent Multi Variate Regression (MVR) model.



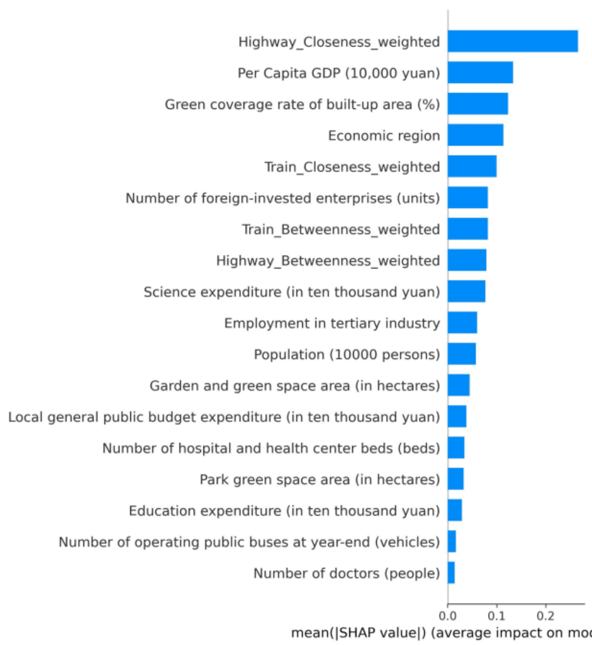


Figure S5: SHAP analysis of a RF machine learning model of residuals around a scaling function predicting social surplus by population (2018, total value of new residential land in a city, priced at auction)

Notes:

a) RF model performance: Training r2=0.89; test R2=0.47; training RMSE=0.45; test RMSE=0.84.

b) Predictors

We attempted to explain urban scaling residuals with factors covering economy (GDP per capita), industrial structure (% tertiary employment), industrial policy (science expenditure by local government), general public expenditure (total government expenditure), social infrastructure (education expenditure), urban morphology (green coverage), complex geography (economic region), simple geography (network connectivity in the national urban system), and others. Population was included to test for heteroscedasticity. Four connectivity measures were used: closeness and betweenness, respectively computed on the national highway and rail network. Closeness measures the degree to which a city is connected to every other city in China's city network. Betweenness measures the density of shortest paths on the network from all cities to all other cities, passing through a city. The network measures were weighted by Euclidian straight line distance between cities, for simplicity.

c) Interpretation

Without connectivity measures and per capita GDP, economic region was the strongest predictor. This is *prima facie* evidence that variance around the urban scaling curve results from complex local processes. 'Economic regions' in China are defined by a mix of geographical, resource, environmental, remoteness, path-dependency, economic and social developmental factors. Adding direct measures of economic output and remoteness (GDP per capita and connectivity) captured a significant portion of the complex economic region effect. Remoteness measured on the highway network is the strongest single predictor of SAMI (direction and quantum of deviation from population-adjusted mean land value). While it is a simple measure, it is also an indicator of all the same complex factors captured in 'economic region'. Being a single measurable quantum, however, it is amenable to change through strategic infrastructure development, and this is significant for policy attempts to move cities up residual distribution and up the entire systems curve. Our finding shows that national highway development is the most important factor influencing the variation of social surplus of Chinese cities of a given size. Per capita GDP systematically increases demand and thus inflates the value of social surplus. Green coverage ratio becomes a more influential predictor of population adjusted social surplus than economic region once the effects of GDP and connectivity are independently accounted for. This is intriguing, probably indicating a particular type of complex local effect manifest in development density, topography, environment and so on. We also note that train network connectedness and industrial structure and policy are correlated in the expected direction with social surplus variation around the size-expected mean.

We report (below) results of the equivalent multi-variate regression model to show that these combined factors only explain ~20% of variation in a traditional statistical analysis. A city's connectivity on the national highway network, measured by both closeness and betweenness centrality, is the most significant explanation of SAMI residuals using MVR, followed by economic region. We take the MVR results to mean two things of interest. First, 80% of the variation in the scaling model remains unexplained, which is an endorsement of the fundamental urban scaling hypothesis that it is the intractable complexities of interactions captured in population size that creates the scale-free performance inflation parameter. Second, it suggests that there is some hope of being able to adjust a city's position on residual and systems curves through policy.

d) MVR results

Model 5

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                                        OLS Regression Results
==============================================================================
Dep. Variable:     SAMI residuals (Tlv-pop 2018)   R-squared:                       0.255
Model:                                       OLS   Adj. R-squared:                  0.159
Method:                            Least Squares   F-statistic:                     2.665
Date:                           Thu, 10 Apr 2025   Prob (F-statistic):           0.000676
Time:                                   12:53:51   Log-Likelihood:                -246.90
No. Observations:                            159   AIC:                             531.8
Df Residuals:                                140   BIC:                             590.1
Df Model:                                     18
Covariance Type:                       nonrobust
==========================================================================================================================
                                                               coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------------------------
const                                                       -1.3004      1.873     -0.694      0.489      -5.004       2.403
Per Capita GDP (10,000 yuan)                                 0.0139      0.023      0.603      0.548      -0.032       0.060
Employment in tertiary industry                             -0.0091      0.009     -0.986      0.326      -0.027       0.009
Economic region                                             -0.2143      0.123     -1.746      0.083      -0.457       0.028
Garden and green space area (in hectares)                 1.161e-05   1.38e-05      0.844      0.400   -1.56e-05    3.88e-05
Park green space area (in hectares)                         -0.0001      0.000     -0.957      0.340      -0.000       0.000
Number of foreign-invested enterprises (units)              -0.0005      0.001     -0.516      0.607      -0.002       0.001
Local general public budget expenditure (in ten thousand yuan) -3.64e-08 1.19e-07 -0.306     0.760   -2.72e-07    1.99e-07
Science expenditure (in ten thousand yuan)                2.045e-07   8.66e-07      0.236      0.814   -1.51e-06    1.92e-06
Education expenditure (in ten thousand yuan)             -1.107e-07   8.84e-07     -0.125      0.900   -1.86e-06    1.64e-06
Number of doctors (people)                                7.605e-05   5.09e-05      1.494      0.137   -2.46e-05       0.000
Number of hospital and health center beds (beds)         -1.376e-05   2.54e-05     -0.543      0.588   -6.39e-05    3.64e-05
Number of operating public buses at year-end (vehicles)  -8.869e-05   9.79e-05     -0.906      0.366      -0.000       0.000
Green coverage rate of built-up area (%)                    -0.0052      0.037     -0.143      0.887      -0.078       0.067
Population (10000 persons)                                   0.0011      0.003      0.434      0.665      -0.004       0.006
Train_Closeness_weighted                                  -859.8678   1565.045     -0.549      0.584   -3954.045    2234.310
Train_Betweenness_weighted                                  -4.4619      4.700     -0.949      0.344     -13.753       4.829
Highway_Closeness_weighted                                4599.3037   1623.552      2.833      0.005    1389.454    7809.154
Highway_Betweenness_weighted                                -7.3903      3.623     -2.040      0.043     -14.553      -0.228
==============================================================================
Omnibus:                       13.275   Durbin-Watson:                   1.910
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               14.318
Skew:                          -0.640   Prob(JB):                     0.000778
Kurtosis:                       3.725   Cond. No.                     2.41e+11
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.41e+11. This might indicate that there are
strong multicollinearity or other numerical problems.
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Supplementary S6: predicted vs observed social surplus

Table S6: Predicted vs actual social surplus for selected Chinese prefecture cities in 2018 (predicted by $Y=Y_0P^{1.13}$)

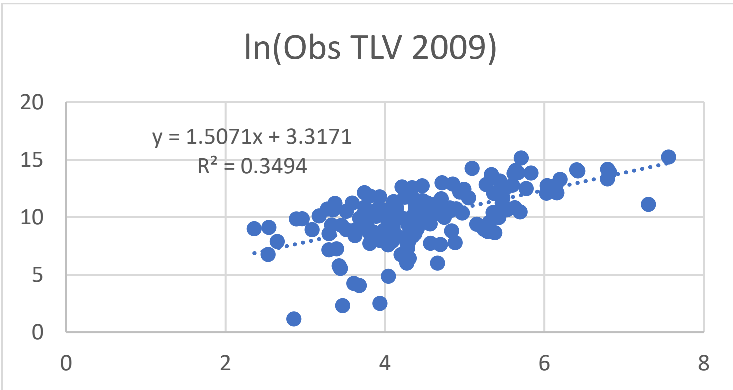
Cities with the 20 highest positive residuals			Cities with the 20 highest negative residuals			Tier 1 cities and cities directly under control of central government		
City	Predicted land value (10,000 RMB)	Actual value (10,000 RMB)	City	Predicted land value (10,000 RMB)	Actual value (10,000 RMB)	City	Predicted land value (10,000 RMB)	Actual value (10,000 RMB)

Ezhou	88413	1320260	Tonghua	88718	14924	Shanghai	7796196	8942894
Huzhou	200989	2480810	Yinchuan	358437	51962	Beijing	5792761	6548200
Jiaxing	164626	1788112	Zhaoqing	170143	22251	Guangzhou	3908660	4108702
Quzhou	66383	701585	Shaoguan	130145	16503	Chongqing	4559846	4061717
Nantong	370477	3852980	Harbin	1269152	149612	Tianjin	3846247	1090240
Lishui	69609	708050	Weihai	205172	19975	Shenzhen	3865854	945150
Taizhou (Zhejiang)	224925	2059532	Benxi	179636	16505			
Zhangzhou	103567	931800	Guangyuan	105007	9617			
Chuzhou	98889	805127	Anshan	316328	28187			
Shangrao	154211	1153186	Daqing	317384	27300			
Shaoxing	339512	2497146	Dalian	963547	45953			
Zhoushan	122246	893766	Hohhot	562466	26377			
Jinan	1063185	6923054	Jixi	136340	5263			
Suzhou (Jiangsu)	896424	5699335	Shuozhou	82872	2370			
Jingdezhen	105029	659804	Yingkou	187149	4602			
Heze	193104	1118563	Foshan	432092	9443			
Jinhua	169371	942684	Shangluo	46947	785			
Zhongshan	113175	618017	Sanya	126494	1266			
Xuancheng	66593	346062	Ordos	103921	600			
Sanming	42667	217050	Hegang	102948	516			

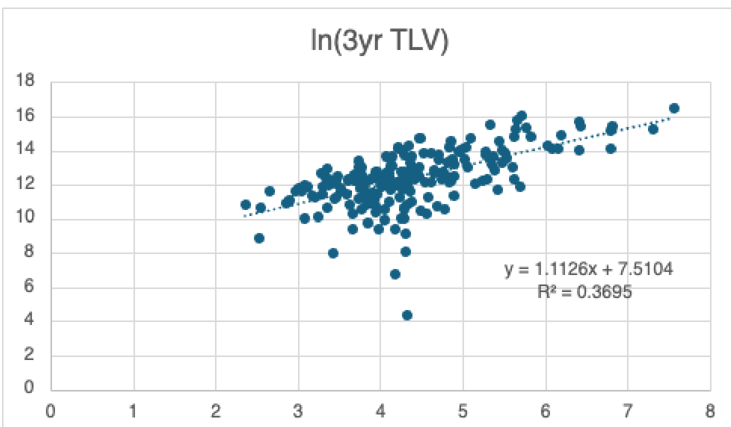
Note (S6): Table S6 includes data for specific cities identical to those listed in Table S2. The actual land value data for all cities is available from the CREIS database (https://creis.fang.com/4.0/), while the predicted land value data for all cities can be obtained from the authors.

Supplementary S7: Sensitivity tests, measuring social surplus over multiple subsequent years (total residential land value priced at auction, summed over 1, 3, 5, 10 and 14 years from 2009, with population in 2009 taken as an indicator of social complexity in that year and creating social surplus in subsequent years).

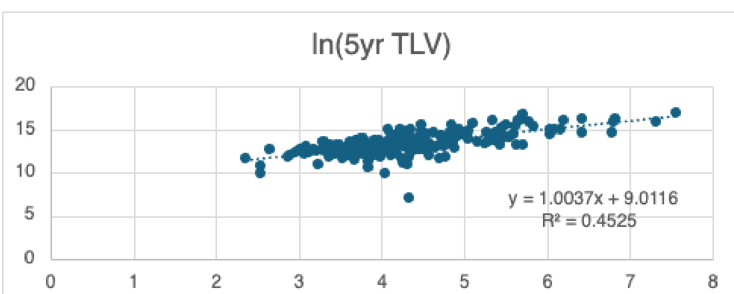
For a sensitivity test, we re-ran scaling models, forward lagging the social surplus measure total over 3, 5, 10 and 14 years. Supplementary Figure S7 shows plots of natural log of total land value created over 1 (beta=1.5), 3 (beta =1.11), 5 (beta=1.0), 10 (beta=0.95) and 14 (beta=0.97) years as a function of natural log of population in 2009. For the year 2018, the 1-year 1.13 beta reduces to 1.11 when modelling a three-year accumulated forward lag of social surplus value, and 0.07 with a five-year lag. We conclude that it is worth researching lag effects more systematically than we are able to in this study. Our test suggests a movement from super-linear towards pro-rata (or marginal sub-linear) increase in social surplus with population as measurement time window is increased.



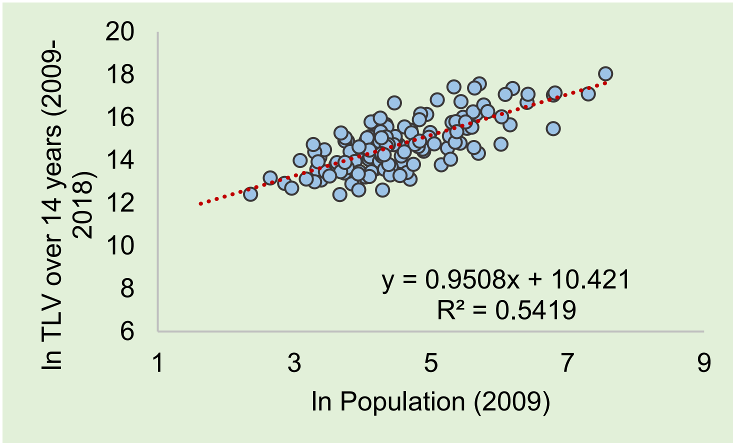
S7(a): ln(total land value over one year, 2009, against ln population in 2009.



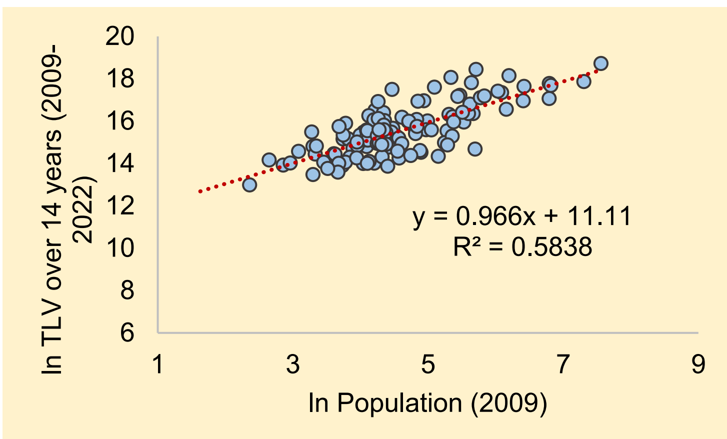
S7(b): ln(total land value over three years, 2009-2011, against ln population in 2009.



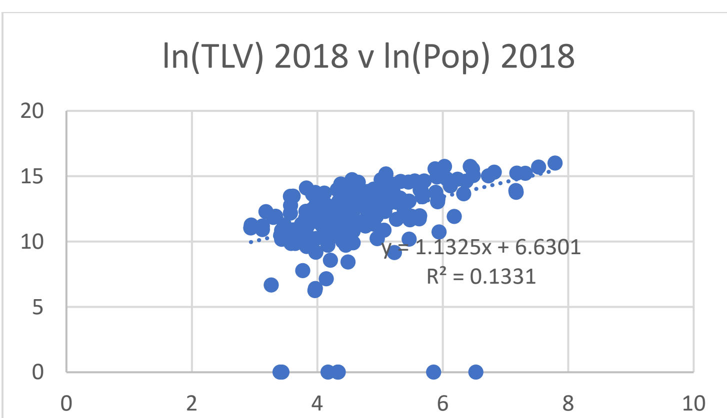
S7(c): ln(total land value over five years, 2009-2013, against ln population in 2009.



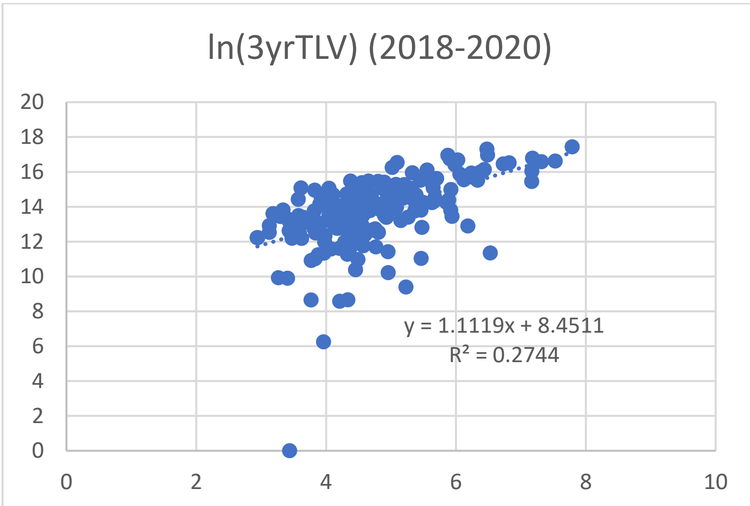
S7(d): ln(total land value over ten years, 2009-2018, against ln population in 2009.



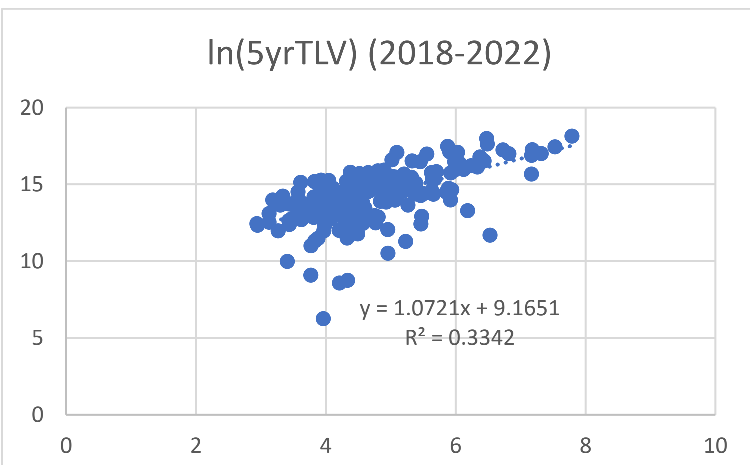
S7(e): ln(total land value over fourteen years, 2009-2022, against ln population in 2009.



S7(f): ln(total land value over one years, 2018, against ln population in 2018.



S7(g): ln(total land value over three years, 2018-2020, against ln population in 2018.



S7(h): ln(total land value over five years, 2018-2022, against ln population in 2018.

Supplementary S8: a note on Ricardo's land value theory.

Ricardo observed unequal land quality leading to differential labour input for a given crop and price, thus yielding unequal surplus value captured by landowners. He also argued that land value rises with population. Von Thunen imagined agricultural land-use patterns determined by different crops, each with their own price and transport costs, grown at different distances from a central market, and surplus production value bid away as land rent. While Karl Marx differed with Ricardo in viewing land rent as a monopolistic production cost earned by the input of capital rather than pure unearned value, both perspectives see landowners as capturing social surplus.

Supplementary S9: a note on the combined effect of super-linear public good benefits and sub-linear public good costs.

The real windfall gains to larger cities are likely to be greater than implied by our beta coefficient, therefore. In China, the municipal state, by and large, seems to use this for social good. This is evidenced in another way by comparing the scaling exponent for GDP in the cities in our study, averaged over the same 14 years, which we calculated to be 1.04, and scaling exponent of public expenditure on research and technology for the same cities (beta=1.15, measured over the 4 years for which we had data). In other words, unearned land value and local government investment rise in line with each other with increasing city size, but GDP (as a measure of productivity) rises significantly more slowly, albeit still super-linearly. Chinese city governments use their windfall to invest, which is efficient if the investment eventually yields economic productivity and welfare growth. China's current property crash happened partly because a lot of municipal investment was too speculative and too consumption-oriented (real estate projects). In that sense, Chinese municipalities share some characteristics with the private landowners who benefit from the land value betterment windfall in cities in most other countries. The fact that Chinese mayors tend to use the windfall for city-aggrandizing schemes means that Chinese cities face the unusual *principal-agent* problem of an *oversupply* of some kinds of urban infrastructure – something it will be dealing with for decades to come.