Supporting Information

Table S1. Composition of the eleven regions used in the study.

Region	Countries in the region
CPA = Centrally planned Asia and China	Cambodia, China (incl. Hong Kong), Korea (DPR), Laos (PDR), Mongolia, Viet Nam
EEU = Central and Eastern Europe	Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, The former Yugoslav Rep. of Macedonia, Hungary, Poland, Romania, Slovak Republic, Slovenia, Yugoslavia
FSU = Newly independent states of the former Soviet Union	Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Republic of Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine, Uzbekistan
LAC = Latin America and the Caribbean	Antigua and Barbuda, Argentina, Bahamas, Barbados, Belize, Bermuda, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, French Guyana, Grenada, Guadeloupe, Guatemala, Guyansa, Haiti, Honduras, Jamaica, Martinique, Mexico, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Santa Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, Venezuela
MNA = Middle East and North Africa	Algeria, Bahrain, Egypt (Arab Republic), Iraq, Iran (Islamic Republic), Israel, Jordan, Kuwait, Lebanon, Libya/SPLAJ, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syria (Arab Republic), Tunisia, United Arab Emirates, Yemen
NAM = North America	Canada, Guam, Puerto Rico, United States of America, Virgin Islands
PAS = Other Pacific Asia	American Samoa, Brunei Darussalam, Fiji, French Polynesia, Gilbert-Kiribati, Indonesia, Malaysia, Myanmar, New Caledonia, Papua, New Guinea, Philippines, Republic of Korea, Singapore, Solomon Islands, Taiwan (China), Thailand, Tonga, Vanuatu, Western Samoa
POECD = Pacific OECD	Australia, Japan, New Zealand
SAS = South Asia	Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka
SSA = Sub-Saharan Africa	Angola, Benin, Botswana, British Indian Ocean Territory, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Cote d'Ivoire, Congo, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Reunion, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Saint Helena, Swaziland, Tanzania, Togo, Uganda, Zaire, Zambia, Zimbabwe
WEU = Western Europe	Andorra, Austria, Azores, Belgium, Canary Islands, Channel Islands, Cyprus, Denmark, Faeroe Islands, Finland, France, Germany, Gibraltar, Greece, Greenland, Iceland, Ireland, Isle of Man, Italy, Liechtenstein, Luxembourg, Madeira, Malta, Monaco, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom

Supporting Materials and Methods

Residential and commercial floor area per capita (FAC) projections to 2050: We build empirical multiple linear regression models to predict residential and commercial FAC, respectively using a panel dataset for 32 energy-economic regions in 1990 and 2000 (Tables S1-S2). Our explanatory variables are GDP per capita (GDPC) and urban population density as well as regional dummies. The scatter plots between the independent variables and the dependent variable indicate a log linear relationship between urban population density (UPD) and FAC, therefore we log transform UPD (Figure S1). However, it is not clear whether the relationship between FAC and GDPC is linear. We compare models with log transformed GDPC and models without transformed GDPC, and find the linear relationship better fit the relationship between FAC and GDPC (R^2: 72% for linear form and 68% for log-linear form for residential FAC, and 69% for linear form and 66% for log-linear model for commercial FAC; all without the regional dummy variables). To keep the regional variation of the effects of GDPC and UPD on FAC, we perform linear regression analysis with region fixed effects, separately, for residential FAC and commercial FAC (Eqns. S1-S2).

$$residentialFAC_{it} = \alpha_0 + \alpha_1 \ln(UPD_{it}) + \alpha_2 GDPC_{it} + \sum_{j=2}^{N} \gamma_j D_{ij} + \varepsilon_{it} \qquad i=1...N,\ t=1990,\ 2000 \qquad (S1)$$

$$commercialFAC_{it} = \beta_0 + \beta_1 \ln(UPD_{it}) + \beta_2 GDPC_{it} + \sum_{j=2}^{N} \delta_j D_{ij} + \zeta_{it} \qquad i=1...N,\ t=1990,\ 2000 \qquad (S2)$$

where α_0, β_0 are constants, $\alpha_1, \alpha_2, \beta_1, \beta_2$ are the coefficients of main explanatory variables to be estimated, γ_j, δ_j are the coefficients of the regional dummies D_{ij}, and ε_{it}, ζ_{it} are error terms. N = 29 since 3 of the 32 regions (Eastern Europe, European Free Trade Association, and Taiwan) are not included in the regression analysis because of lack of data. We run two versions of the above models: the first, employing regular panel regression utilizing dummy variables and the second adjusting the estimation process for the use of robust standard errors.

Diagnostics of the regression models: Four principal assumptions (i.e., linearity and additivity, statistical independence, homoscedasticity of errors, and normality of error distribution) justify the use of linear regression models for our purposes of inference or prediction. The diagnostics of our regression models are listed below.

Testing for linearity and additivity: We plot the residuals against the fitted values to check for the linearity and additivity (Figures S2-S3). Nonlinearities may be present when there is a systematic relationship between the two: low residuals with low fitted values and high residuals with high fitted values. The red lines that pass through the scatterplots show that there is not such a relationship for either the residential or the commercial model. The residuals of the residential model scatter around zero with constant variance indicating the assumption is satisfied (Figure S2). For the commercial model, the residuals scatter around zero but with a pronounced increase in variance: this "megaphone" pattern in the residual vs fitted plot shows a problem of heteroscedasticity, which we correct as detailed below (Figure S3).

Testing for independence of errors: The problem of serial correlation of errors is present in long time-series regression analysis (a problem of correlation of errors across time periods or seasonal correlations). In our case, we employ a pooled regression analysis for the cross-sectional observations with only two time periods; thus, we expect this problem to be minimized for the time dimension. Autocorrelation may also be present in space (spatial autocorrelation). We visually inspect residuals of the residential and commercial model against our regressors (Figure S4) and do not identify any systematic behavior of the residuals. We thus do not find evidence for challenging the assumption of zero covariance in the error term.

Testing for normality of errors: We examine the assumption for the normality of errors by examining the residuals and generating a Q-Q plot which plots order statistics of residuals against the quantiles of a standard normal distribution N(0,1). We find that the Q-Q plots for our two models is reasonably straight (Figures S2-S3). We interpret this as evidence that the normality assumption holds; thus, regression statistics such as the *t* and *F* tests should not be affected.

Testing for heteroskedasticity: Normality is not the only assumption that can affect our hypothesis tests. Plotting the regression residuals against our main explanatory variables (log population density and GDP per capita) provides a first visual test for heteroskedasticity; the plots reveal a potential problem with the classical homoscedasticity assumption as the dispersion around the residual mean of zero is affected by whether the values of our explanatory variables are high or low (Figure S4). GDPC appears to be the main culprit for the non-constant variance problem. We also verify that heteroskedasticity is an issue by examining the plots of residuals vs fitted values (Figure S3). The problem seems more pronounced in the commercial FAC model. Heteroskedasticity affects the statistical significance of our regression coefficients and needs to be accounted for in our models. We describe the process of correction of this problem below.

Testing for no multicollinearity: In regression analysis, perfect multicollinearity between variables is a serious problem and we typically desire little to no multicollinearity. Using simple correlation measures, we find that the correlation coefficient between the log urban population density and GDPC is significant, but the magnitude is low (Pearson correlation = -0.34). Furthermore, we calculated Variance Inflation Factor (VIF) –without the regional dummies– for the two independent variables, which are 3.72 and 3.29 for residential FAC and commercial FAC, respectively. We interpret these low values as showcasing no multicollinearity. We do not calculate VIF with the regional dummies because research shows that the VIF with dummies is not a reliable indicator of collinearity (1).

Correction for heteroskedasticity: We correct our heteroskedasticity issues (and the resulting high standard errors in the original regressions) by using covariance matrix estimators that consistently estimate the covariance of the model parameters – the so-called 'sandwich' estimator (Tables S3-S4). The panel regressions with robust standard errors produce coefficients for population density that are statistically significant at the 1% level or below (Tables S3-S4). But in the commercial model, GDPC is now not statistically significant at any reasonable level. Note that the correction for heteroskedasticity only affects standard errors and the coefficients and their interpretation remains the same.

Interpretation of coefficients: Having run all the above tests, we can go ahead with the interpretation of our regression coefficients. Both urban population density and GDPC have a significant effect (in terms of magnitude) on residential FAC and commercial FAC. Furthermore, the majoring of our regional dummies have significant (statistically and in magnitude) effects on residential and commercial FAC. Increasing incomes will increase FAC ceteris paribus, assuming that living space is a normal good. Increases in urban population density will decrease FAC. In particular, our models show that a 10% increase in urban population density leads to a drop of the expected residential FAC by 0.158 units and a drop of the expected commercial FAC by 0.342 units. The panel regression models explain 97.6% and 98.8% of the variation of the residential FAC and commercial FAC, respectively (Tables S3-S4).

Residential and commercial FAC projections:

We build three scenarios of urban population density projection to 2050 based on urban population density in 2000 and the historical urban population density change rate from 1970 to 2000. We first calculate annual urban population density change rate for each decade at the city level using the datasets of Angel et al. (2012) (2) and Seto et al. (2011) (3). Then, aggregating our findings to each of the 32 regions, we fit a probability density function (PDF) of the distribution of the calculated annual urban population change rate assuming a generalized logistic distribution of urban population density change rate (Figure S5). From the PDF of each region, we draw the low (25%), medium (50%), and high (75%) annual urban population density change. Taking 2000 as the base year, we estimate urban population density for each region in five-year intervals into the future up to 2050 for the three scenarios of annual urban population density change rate. For regions with few or no cities sampled, we use PDF of the region with a similar socioeconomic background. Thus, the PDFs of USA, EU-12, EU-15, South Asia, Africa South, and Japan was applied to Australia and New Zealand, Eastern Europe, European Free Trade Association, Pakistan, South Africa, and Taiwan, respectively.

Using the fitted parameter values of the regression model, we generate three scenarios of how residential FAC and commercial FAC are expected to change by 2050 for each region following the low, medium, and high levels of urban population density change rate and GDPC from the forecasts of GDP growth (4) and population growth (5). We do not build a regression model for Eastern Europe, European Free Trade Association, and Taiwan because of the absence of relevant urban population data. Instead, we use the models of the regions with similar socioeconomic characteristics, i.e., EU-12, EU-15, and Japan, respectively.

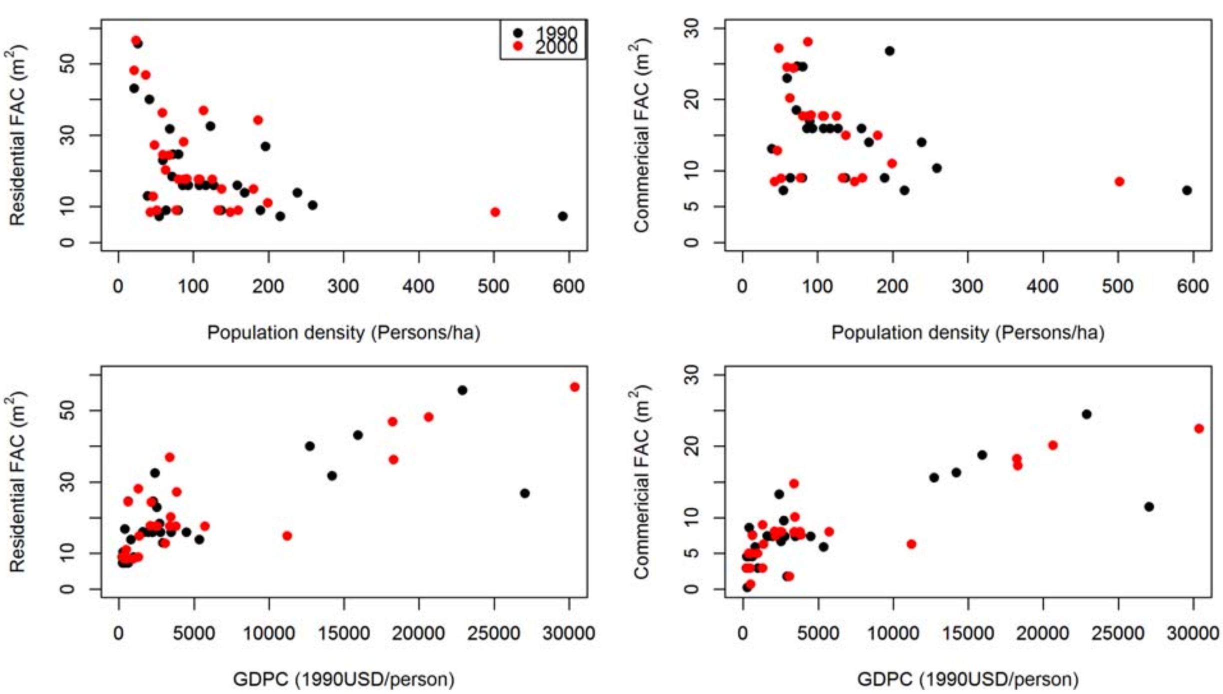


Figure S1. Scatter plot between FAC and urban population density and GDPC in 1990 and 2000.

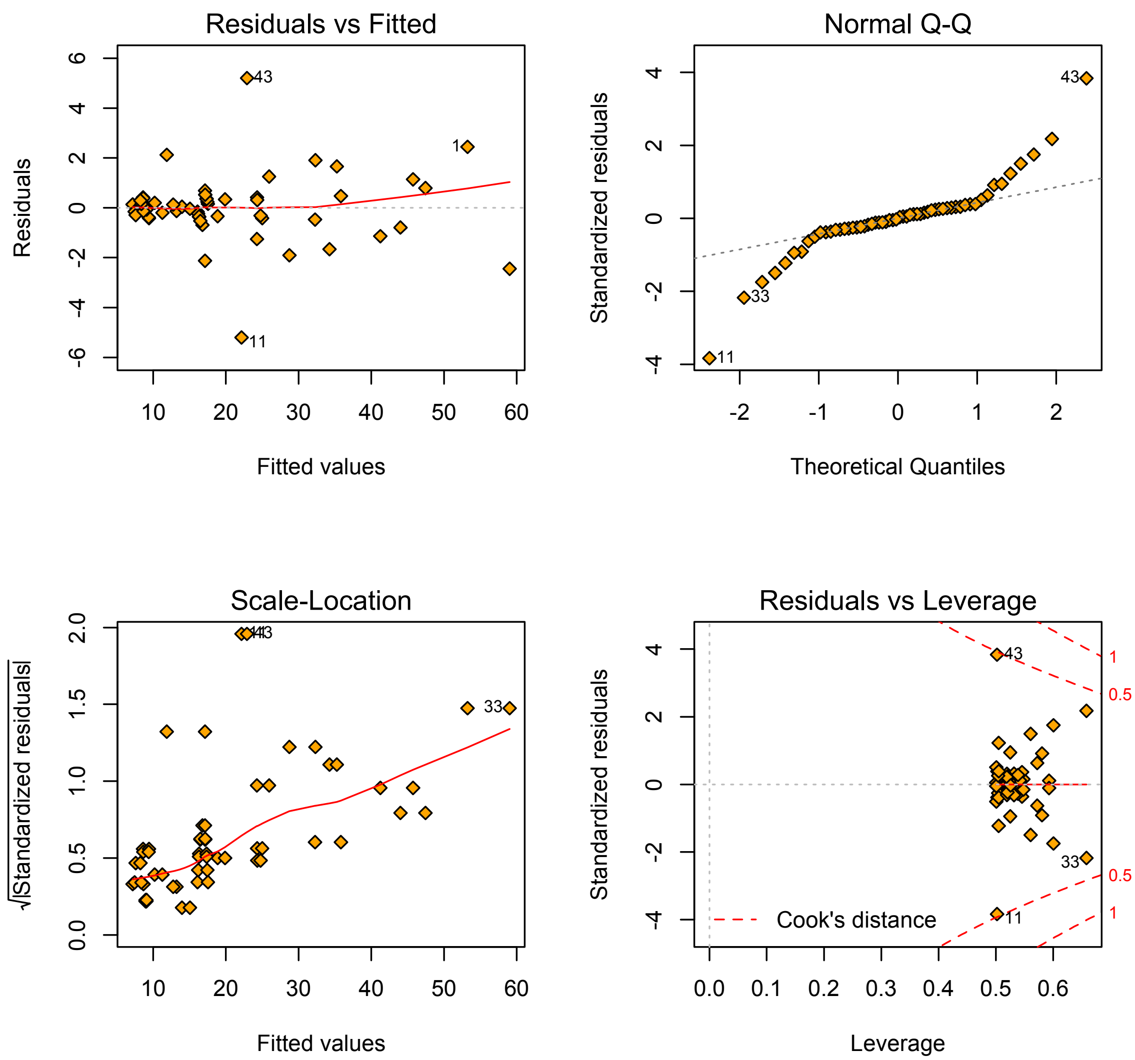


Figure S2. Regression diagnostics for residential FAC model (residuals vs. fitted values, Q-Q plot, scale-location and residuals vs leverage).

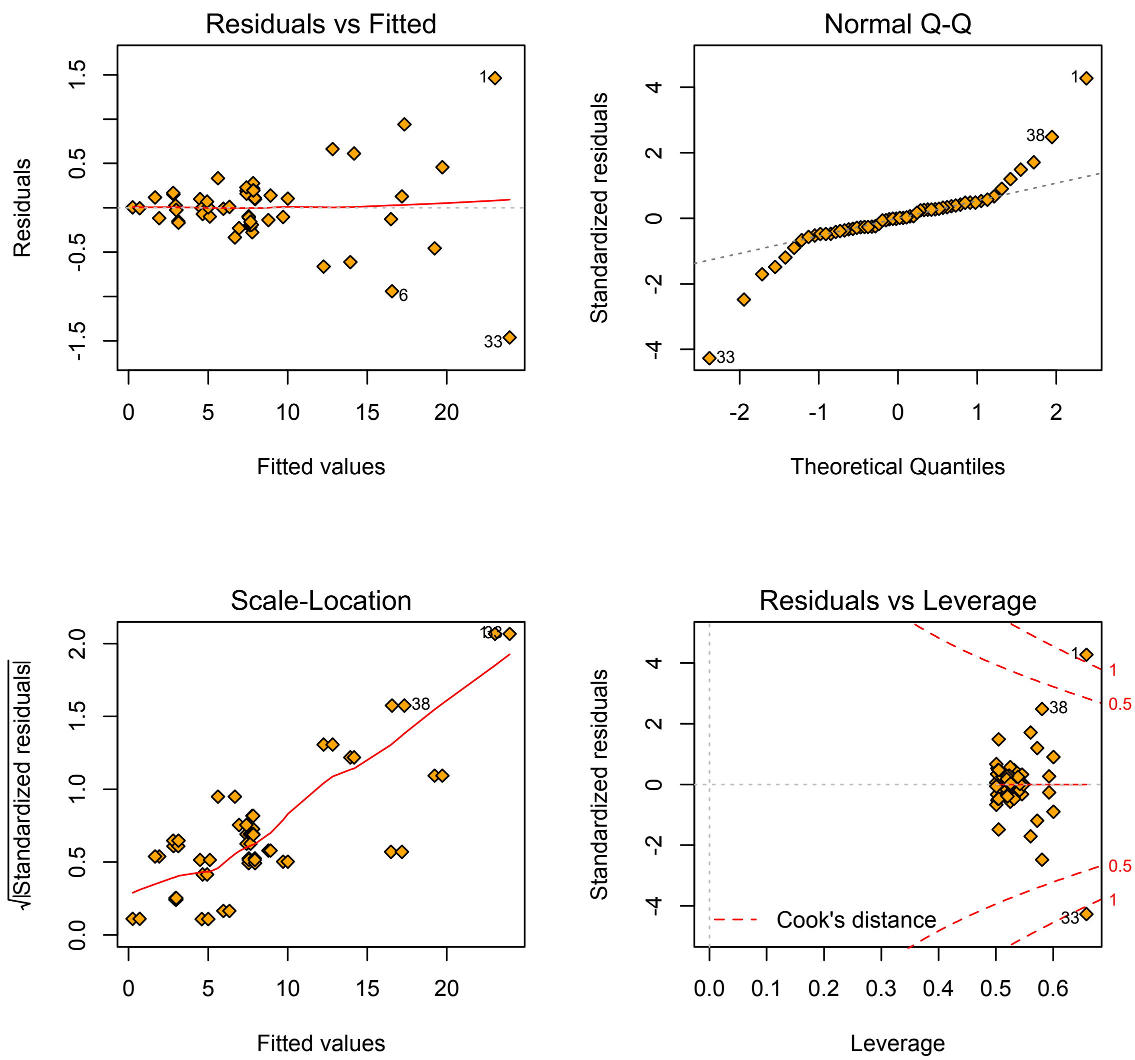


Figure S3. Regression diagnostics for commercial FAC model (residuals vs. fitted values, Q-Q plot, scale-location and residuals vs leverage).

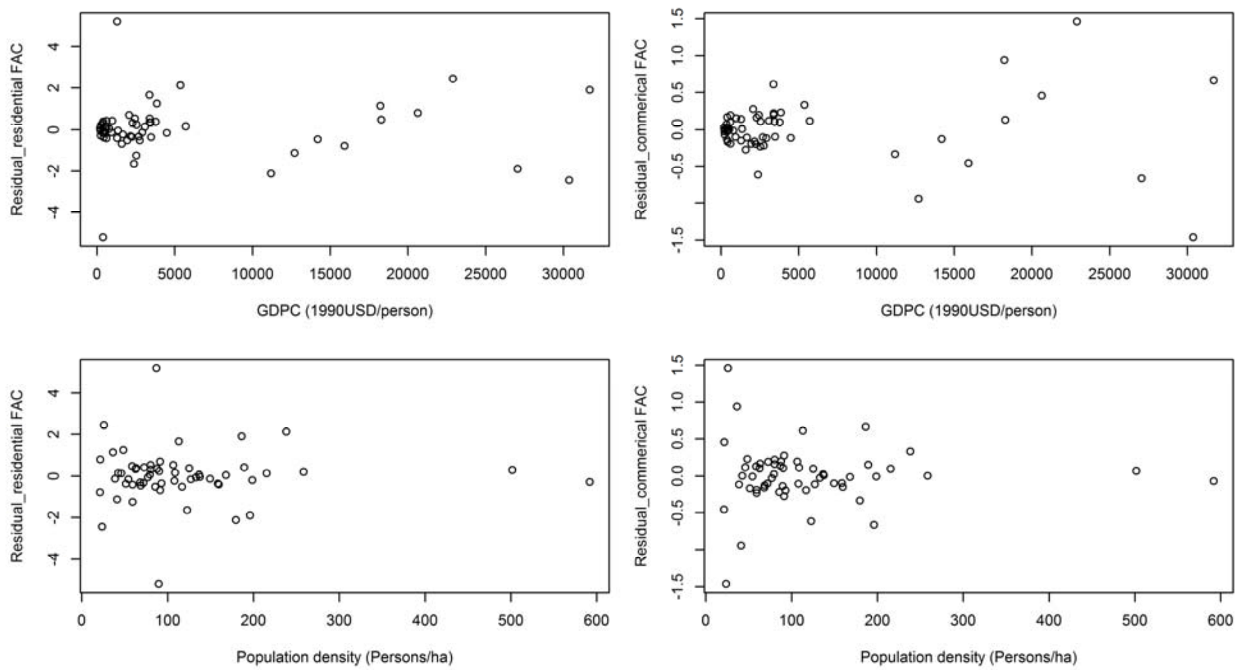
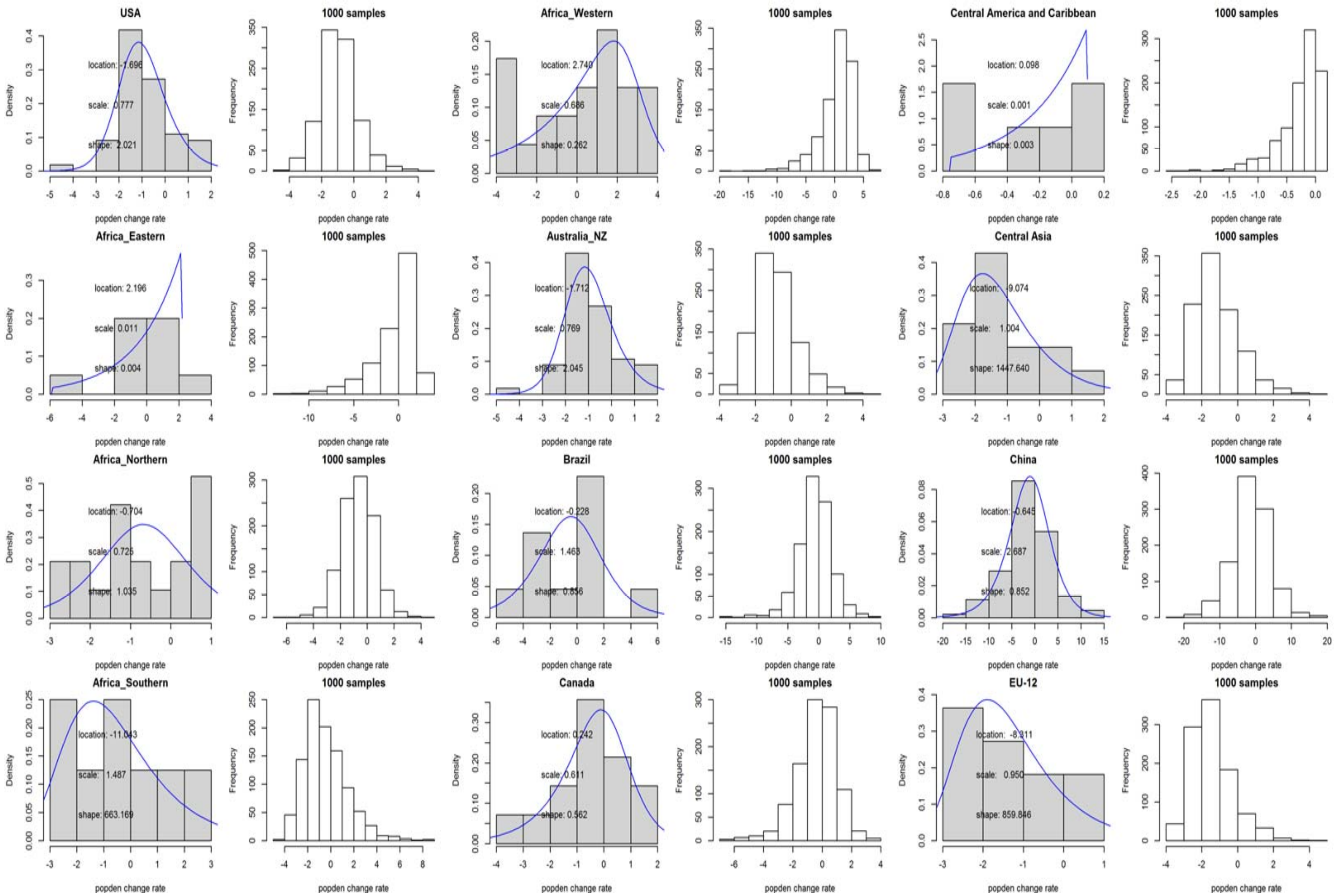
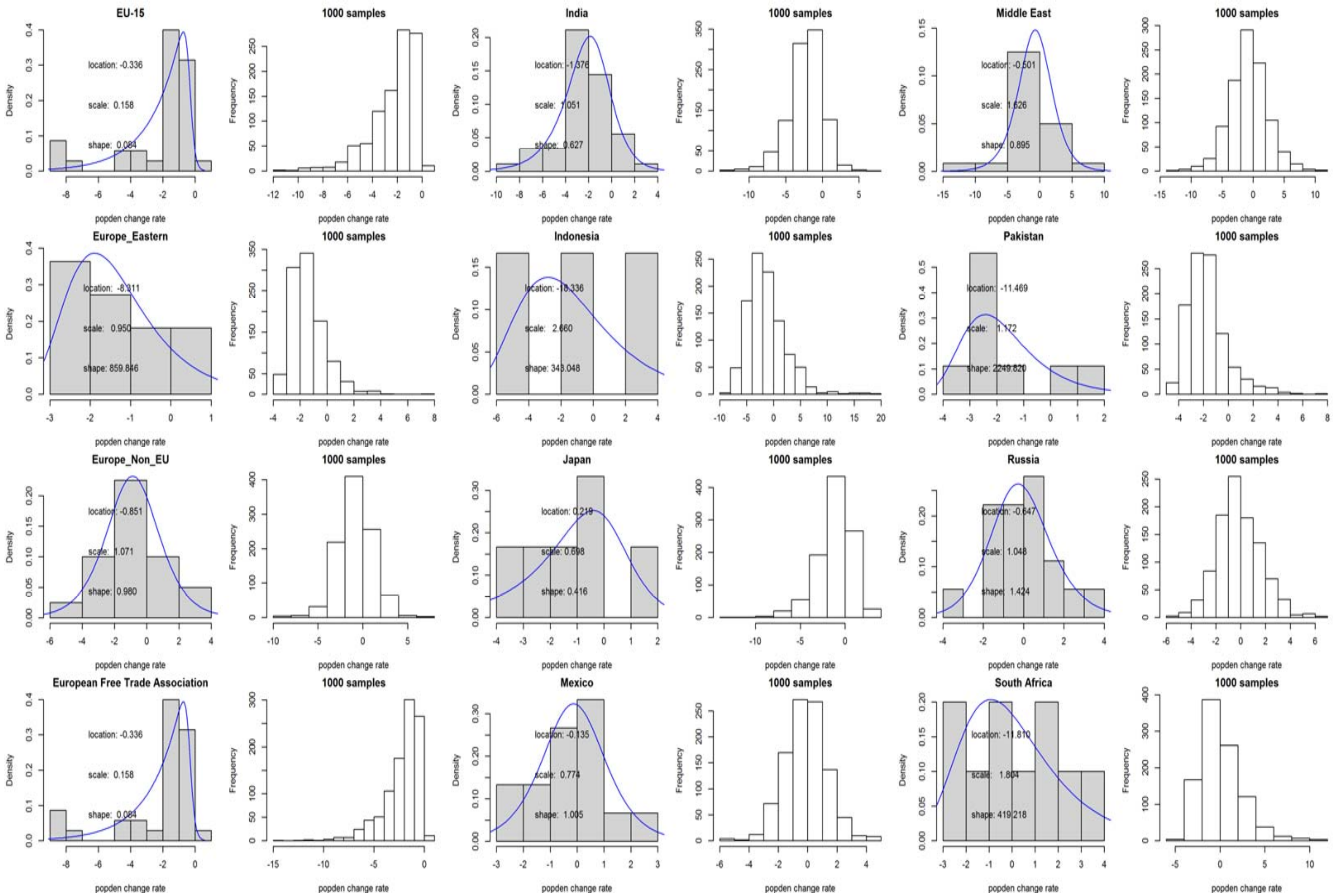


Figure S4. Regression diagnostics for the models to predict FAC (residuals vs. population density and GDPC).


USA
location: -1.696
scale: 0.777
shape: 2.021
1000 samples
Africa_Western
location: 2.740
scale: 0.686
shape: 0.262
Central America and Caribbean
location: 0.098
scale: 0.001
shape: 0.003
Africa_Eastern
location: 2.196
scale: 0.011
shape: 0.004
Australia_NZ
location: -1.712
scale: 0.769
shape: 2.045
Central Asia
location: -9.074
scale: 1.004
shape: 1447.640
Africa_Northern
location: -0.704
scale: 0.725
shape: 1.035
Brazil
location: -0.228
scale: 1.463
shape: 0.856
China
location: -0.645
scale: 2.687
shape: 0.852
Africa_Southern
location: -11.043
scale: 1.487
shape: 663.169
Canada
location: 0.242
scale: 0.611
shape: 0.562
EU-12
location: -8.311
scale: 0.950
shape: 859.846
Density
Frequency
popden change rate



EU-15
location: -0.336
scale: 0.158
shape: 0.084
1000 samples
India
location: -1.376
scale: 1.051
shape: 0.627
1000 samples
Middle East
location: -0.501
scale: 1.626
shape: 0.895
1000 samples
Europe_Eastern
location: -8.311
scale: 0.950
shape: 859.846
1000 samples
Indonesia
location: -18.336
scale: 2.660
shape: 343.048
1000 samples
Pakistan
location: -11.469
scale: 1.172
shape: 2249.820
1000 samples
Europe_Non_EU
location: -0.851
scale: 1.071
shape: 0.980
1000 samples
Japan
location: 0.219
scale: 0.698
shape: 0.416
1000 samples
Russia
location: -0.647
scale: 1.048
shape: 1.424
1000 samples
European Free Trade Association
location: -0.336
scale: 0.158
shape: 0.084
1000 samples
Mexico
location: -0.135
scale: 0.774
shape: 1.005
1000 samples
South Africa
location: -11.810
scale: 1.804
shape: 419.218
1000 samples
Density
Frequency
popden change rate

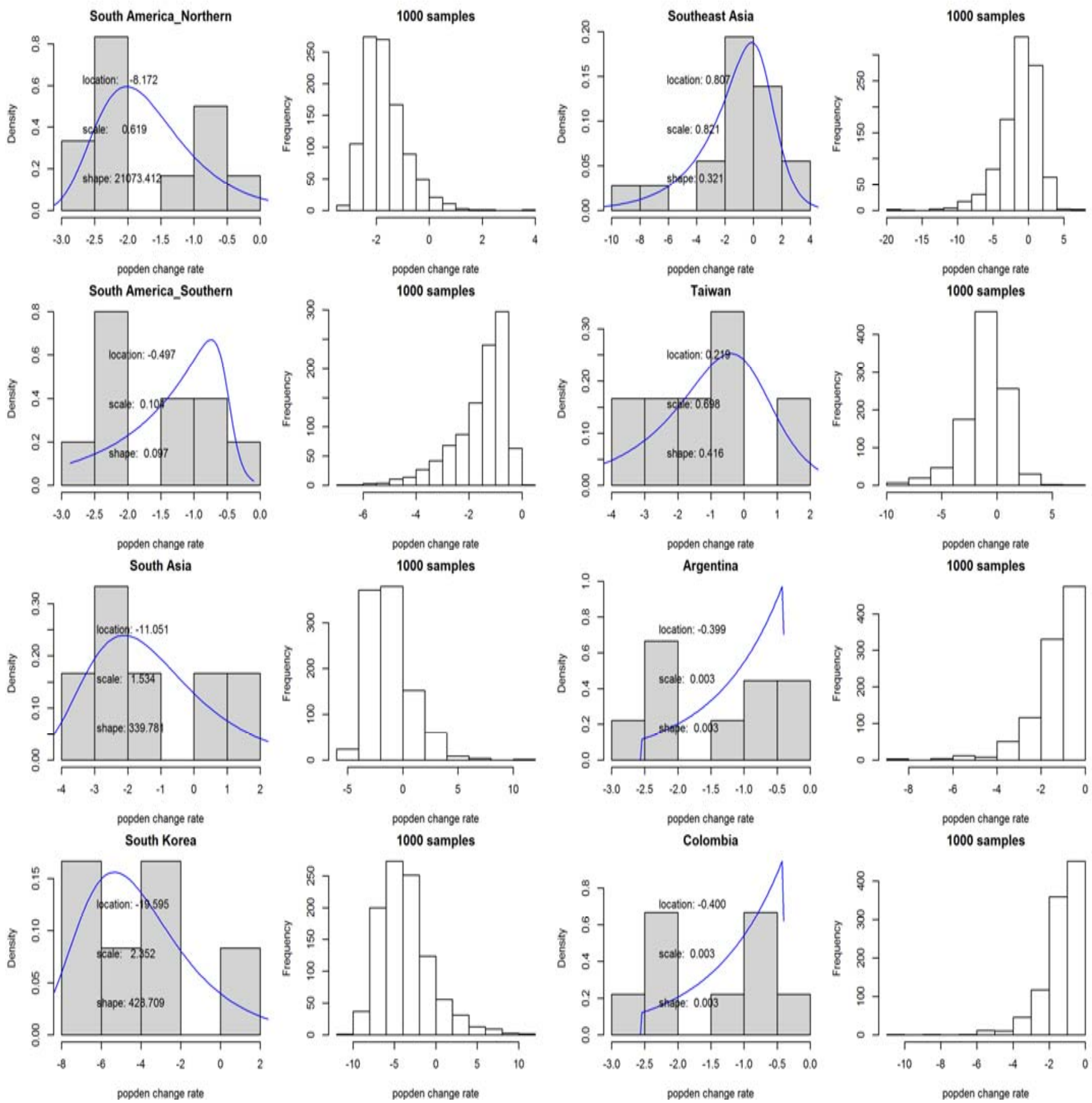


Figure S5. Probability density functions of regional urban population density change rates.

Table S2. Statistical summary of the data used to building the regression model.

	Min	**Mean**	**Max**	**SD**
1990				
Residential FAC (m^2/person)	7.30	19.29	55.69	11.81
Commercial FAC (m^2/person)	0.26	8.00	24.49	5.37
GDPC1990 (1990USD/person)	193.60	5191.00	27059.90	7586.64
Population density (persons/ha)	21.15	126.24	591.80	109.45
2000				
Residential FAC (m^2/person)	8.54	21.49	56.59	13.10
Commercial FAC(m^2/person)	0.69	8.51	22.48	5.51
GDPC2005 (1990USD/person)	223.60	6895.30	31687.40	9579.23
Population density (persons/ha)	21.34	107.94	501.61	90.02

Table S3. Results of panel regression for residential FAC.

	Before correcting for heteroskedasticity				After correcting for heteroskedasticity			
	coefficients	Std Error	t value	P	coefficients	Std Error	t value	P
(Intercept)	25.65	16.15	1.59	0.12	25.65	5.43	4.72	<0.01
Ln(population density)	-3.42	3.28	-1.04	0.31	-3.42	1.10	-3.10	<0.01
GDPC	0.00074	0.00022	3.40	<0.00	0.00074	0.00019	3.70	<0.01
Africa_Eastern	(baseline)							
Africa_Northern	0.19	2.14	0.09	0.93	0.19	0.49	0.38	0.70
Africa_Southern	-3.10	3.40	-0.91	0.37	-3.10	0.97	-3.18	<0.01
Africa_Western	-1.99	2.62	-0.76	0.45	-1.99	0.60	-3.35	<0.01
Argentina	4.52	2.26	2.00	0.06	4.52	0.59	7.64	<0.01
Australia_NZ	18.95	4.50	4.21	<0.01	18.95	2.92	6.48	<0.01
Brazil	4.03	2.41	1.67	0.11	4.03	0.72	5.61	<0.01
Canada	17.08	6.01	2.84	0.01	17.08	3.43	4.99	<0.01
Central America and Caribbean	5.41	2.25	2.40	0.02	5.41	0.65	8.34	<0.01
Central Asia	12.85	3.02	4.25	<0.01	12.85	0.82	15.59	<0.01
China	11.59	2.34	4.95	<0.01	11.59	3.70	3.13	<0.01
Colombia	5.69	2.01	2.83	0.01	5.69	0.53	10.81	<0.01
EU-12	10.73	3.42	3.14	<0.01	10.73	1.31	8.21	<0.01
EU-15	10.63	3.84	2.76	0.01	10.63	2.99	3.55	<0.01
Europe_Non_EU	23.31	2.00	11.64	<0.01	23.31	1.27	18.30	<0.01
India	3.38	2.58	1.31	0.20	3.38	0.60	5.58	<0.01
Indonesia	-0.53	2.16	-0.24	0.81	-0.53	0.39	-1.37	0.18
Japan	1.21	7.13	0.17	0.87	1.21	6.13	0.20	0.85
Mexico	3.73	2.15	1.73	0.09	3.73	0.93	3.99	<0.01
Middle East	5.85	2.86	2.05	0.05	5.85	0.80	7.33	<0.01
Pakistan	-4.81	3.87	-1.24	0.22	-4.81	1.13	-4.27	<0.01
Russia	11.98	2.66	4.51	<0.01	11.98	0.67	17.96	<0.01
South Africa	-2.07	4.08	-0.51	0.62	-2.07	1.19	-1.74	0.09
South America_Northern	5.44	2.09	2.61	0.01	5.44	0.75	7.26	<0.01
South America_Southern	5.34	2.14	2.50	0.02	5.34	0.44	12.22	<0.01
South Asia	3.62	4.97	0.73	0.47	3.62	1.56	2.31	0.03
South Korea	1.00	3.28	0.31	0.76	1.00	2.38	0.42	0.68
Southeast Asia	5.25	1.99	2.65	0.01	5.25	0.26	20.18	<0.01
USA	21.84	6.41	3.41	<0.01	21.84	5.16	4.24	<0.01
	Adjusted R-squared: 0.976				Adjusted R-squared: 0.976			

Table S4. Results of panel regression for commercial FAC.

	Before correcting for heteroskedasticity				After correcting for heteroskedasticity			
	coefficients	Std Error	t value	P	coefficients	Std Error	t value	P
(Intercept)	10.73	4.92	2.18	0.04	10.73	2.30	4.67	<0.01
Ln(population density)	-1.59	1.00	-1.59	0.12	-1.59	0.46	-3.41	<0.01
GDPC	0.00011	0.00006	1.60	0.12	0.00011	0.00011	1.00	0.33
Africa_Eastern	(baseline)							
Africa_Northern	0.30	0.65	0.47	0.64	0.30	0.23	1.31	0.20
Africa_Southern	-1.39	1.04	-1.34	0.19	-1.39	0.40	-3.47	<0.01
Africa_Western	-0.88	0.80	-1.11	0.28	-0.88	0.24	-3.67	<0.01
Argentina	3.84	0.69	5.57	<0.01	3.84	0.21	17.88	<0.01
Australia_NZ	10.37	1.37	7.56	<0.01	10.37	1.36	7.63	<0.01
Brazil	3.69	0.74	5.02	<0.01	3.69	0.23	15.81	<0.01
Canada	11.66	1.83	6.36	<0.01	11.66	1.34	8.69	<0.01
Central America and Caribbean	4.04	0.69	5.87	<0.01	4.04	0.22	18.09	<0.01
Central Asia	3.42	0.92	3.71	<0.01	3.42	0.33	10.33	<0.01
China	5.14	0.71	7.19	<0.01	5.14	0.18	28.92	<0.01
Colombia	4.26	0.61	6.95	<0.01	4.26	0.20	21.05	<0.01
EU-12	2.42	1.04	2.32	0.03	2.42	0.30	8.14	<0.01
EU-15	10.97	1.17	9.36	<0.01	10.97	1.43	7.69	<0.01
Europe_Non_EU	10.58	0.61	17.32	<0.01	10.58	0.49	21.50	<0.01
India	-1.69	0.79	-2.16	0.04	-1.69	0.26	-6.62	<0.01
Indonesia	2.22	0.66	3.37	<0.01	2.22	0.20	11.27	<0.01
Japan	7.03	2.17	3.23	<0.01	7.03	3.26	2.16	0.04
Mexico	4.03	0.66	6.15	<0.01	4.03	0.47	8.52	<0.01
Middle East	5.47	0.87	6.28	<0.01	5.47	0.20	26.90	<0.01
Pakistan	0.17	1.18	0.14	0.89	0.17	0.46	0.36	0.72
Russia	3.40	0.81	4.19	<0.01	3.40	0.20	17.29	<0.01
South Africa	-3.32	1.24	-2.66	0.01	-3.32	0.35	-9.42	<0.01
South America_Northern	4.48	0.64	7.04	<0.01	4.48	0.39	11.63	<0.01
South America_Southern	4.07	0.65	6.25	<0.01	4.07	0.14	29.13	<0.01
South Asia	4.03	1.52	2.66	0.01	4.03	0.66	6.12	<0.01
South Korea	3.00	1.00	3.00	0.01	3.00	1.05	2.85	0.01
Southeast Asia	3.27	0.61	5.41	<0.01	3.27	0.14	23.05	<0.01
USA	15.02	1.95	7.68	<0.01	15.02	2.43	6.19	<0.01
	Adjusted R-squared: 0.988				Adjusted R-squared: 0.988			

Top-down model

The Global Change Assessment Model (GCAM) is a partial equilibrium, dynamic-recursive model with a technology-rich representation of energy production, transformation, and consumption. The model is disaggregated into 32 energy-economy regions, 283 land use regions, and 233 water basins globally. Energy consumption and emissions outcomes from GCAM are driven by assumptions of population, labor participation rates, labor productivity, representation of resources, and technologies. GCAM is open-source software; the model used in this study along with assumptions and model inputs are available online (http://www.globalchange.umd.edu/models/gcam/). The population and GDP growth assumptions used in this paper are the same as those of the Medium Reference-No Policy scenario in (6). GCAM considers how changes in socioeconomic drivers, floor area, technology, and climate affect future building energy demand, and it has been used to study future building energy demand at global, national, and sub-national levels (7-9). It is worth noting that GCAM is not used to predict future building energy demand globally or regionally; rather, it adds value by showing the potential impacts of technology improvement and, in this study, also urban density, on building energy use. In this study, we aggregate the original 32 energy-economy regions to 11 in line with the regional break-down of the International Energy Agency (IEA) to facilitate comparison with the bottom-up analysis (Table S5).

Among several factors that affect building energy demand in GCAM, building floor area is the most important. In this study, we use GCAM version 4.2 with the building sector disaggregated into residential and commercial buildings. Detailed information of model description, structure, and data are provided in (4, 10, 11). In GCAM, commercial buildings are already assumed to only exist in urban areas. Although GCAM does not differentiate between urban and non-urban residential buildings, in this study we use urban population projections, urban population density estimates, and GDP projections to project the change in building floor area by 2050 in a given region. Thus, we effectively restrict the output of GCAM for residential buildings to urban areas.

We define two energy-efficiency scenarios for residential and commercial buildings to be analyzed by GCAM:

1. Business-as-usual scenario (BAU) represents a reference case whereby energy efficiency improvements in buildings are autonomous; that is, efficient technologies are deployed without policy intervention.

2. Advanced energy-efficiency scenario (ADV) represents a case with faster improvement in building technologies compared to the BAU scenario. The improvement rate varies between conventional and emerging technologies.

The data and assumptions for the BAU scenario are the default values in GCAM (11). The BAU scenario depicts a world with global population close to 9 billion people, global GDP grows an order of magnitude, and global primary energy consumption is tripled by 2100. There is no policy in mitigating carbon emissions in the BAU scenario with fossil fuels dominated in global energy consumption. However, there is still substantial growth in nuclear and renewable energy (12). The model uses residential and commercial floor area per capita (FAC) projections that we developed for this study.

The ADV scenario assumes faster energy efficiency improvement for all regions than is the case in the BAU scenario. In the ADV scenario, the energy efficiency improvement rate for the United States is assumed to be 0.1% per year for conventional technologies and between 0.25% and 0.75% for emerging technologies; shell efficiency is assumed to improve at 0.65% per year for residential buildings and 0.6% per year for commercial buildings (13). Compared with the BAU scenario, all regions would have higher electrification rate in the advanced technology scenario, and the impact is greater for less developed regions. The use of traditional biomass would be reduced under the advanced technology scenario but a significant amount of traditional biomass would still be consumed in some African regions.

All other inputs and parameters are the same between the BAU and ADV scenarios. In both scenarios, the energy efficiency improvement rates are slightly different across regions, depending on their economic growth and heating/cooling degree days (for shell efficiency). In general, OECD countries such as Canada, Western European countries, Japan, Australia, and Korea follow similar technology improvement rates as the one in the United States. The emerging economies, such as China and Brazil, have lower technology improvement rate, compared to that in the United States. The less developed regions like Africa are assumed to have the slowest technology improvement, constrained by both technology development and institutional factors.

Table S5. Aggregation of the original 32 energy-economic regions in GCAM to IEA regions in the top-down analysis in this study.

GCAM regions	IEA regions in the top-down analysis
China, Taiwan	CPA
Europe_Eastern	EEU
Russia, Central Asia	FSU
Central America and Caribbean, Mexico, Brazil, Argentina, Colombia, South America_Northern, South America_Southern	LAC
Middle East, Africa_Northern	MNA
USA, Canada	NAM
Southeast Asia, Indonesia, South Korea	PAS
Australia & New Zealand, Japan	POECD
Africa_Eastern, Africa_Southern, Africa_Western, South Africa	SSA
Pakistan, South Asia	SAS
EU_12, EU_15, Europe_Non_EU, European Free Trade Association	WEU

Bottom-up model

Heating and cooling energy consumption for the analysis is undertaken using 3CSEP HEB (Center for Climate Change and Sustainable Energy Policy High Efficiency Buildings) model. Although it is an engineering-economic model, it was soft-linked to the “Message” Integrated Assessment model (IAM) of IIASA during the Global Energy Assessment modeling work (14), and thus, it was harmonized with an IAM. Most of its macroeconomic and socio-demographic inputs (population, urbanization rate, etc) are from a consistent set of Message scenarios.

The model, 3CSEP HEB, has a comprehensive multi-level building type classification. Building categories are distinguished by their location (urban, rural, slum), building type (single-family, multifamily, commercial and public buildings with subcategories), building vintage (existing, new, advanced new, retrofit, advanced retrofit), and 17 climate types based on heating, cooling, and dehumidification needs. A detailed description of the model can be found in (15), with some key overviews published in (16).

One of the main goals of the model is to interrogate the extent to which global heating and cooling energy use could be brought down if today's best practice buildings were proliferated ubiquitously after a certain transition time for markets and policies to adjust. Hence this state-of-the-art scenario (deep efficiency scenario) resonates the "technical potential" concept from engineering economic forecasting analyses; nevertheless, its input data are, where possible, based on actual, ex-post data from existing best-practice buildings.

The three fundamental scenarios of energy efficiency we used in the bottom-up model:

Frozen Efficiency Scenario: Frozen Efficiency scenario assumes that the energy performance of new and retrofit buildings do not improve as compared to their 2005 levels and retrofit buildings consume around 10% less than standard existing buildings for space heating and cooling, while most of new buildings have higher level of energy consumption than in the moderate scenario due to lower compliance with building codes.

Moderate Efficiency Scenario: The rationale for this scenario is to illustrate the development of the building energy use taking into account current policy initiatives, such as building codes for new buildings. The scenario assumes a slightly accelerated renovation dynamic (i.e. the share of buildings reconstructed annually) to reflect that many countries recognized the importance of the quick implementation of energy-efficient retrofits and energy-efficient building codes.

Deep Efficiency Scenario: This scenario demonstrates how far today's state-of-the-art construction and retrofit know-how and technologies can take the building sector in reducing energy use, while also providing full thermal comfort in buildings. It assumes that, after a short period of market transformation, today's best practice in both new construction and retrofit becomes the standard. In essence, we determine the techno-economic energy efficiency potentials in the building sector.

Under each of the base scenarios above, two different retrofit dynamics are assumed to unfold into the future:

Variant 1: Retrofit rate increases linearly from 1.4% to 3% until 2025 and then stays at 3% until 2050.

Variant 2: Moderate scenario: retrofit rate increases in 5 years (i.e., in 2020) to 5%; Deep scenario: retrofit rate stays at 1.4% until 2025, then it increases to 5%.

The fundamental scenarios differ very much in their assumptions on the penetration of efficient buildings. Each assume different transitionary periods for the markets to be able to deploy 100% advanced buildings, as well as different trajectories in the acceleration of the retrofit rate. Frozen efficiency scenario simply means the same efficiency level buildings get to be built and retrofitted as today. In contrast, moderate efficiency scenario assumes there is a push in policies towards retrofits, but the energy savings of the retrofits, *ret*, and new buildings, *new*, stay moderate. It does assume some limited autonomous penetration of advanced new (*anew*) and advanced retrofitted (*aret*) buildings, especially in Europe (where it is already the law), where these achieve more noticeable levels. Deep efficiency scenario assumes that after a transitionary period (10 years) for markets to fully adopt the know-how, all *new* and *ret* will become *anew* and *aret* (except a small portion that is physically not possible, such as historic buildings, although by today we have evidence that even these can achieve passive standards).

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