Supplementary Information

Urban land expansion: the role of population and economic growth for 300+ cities

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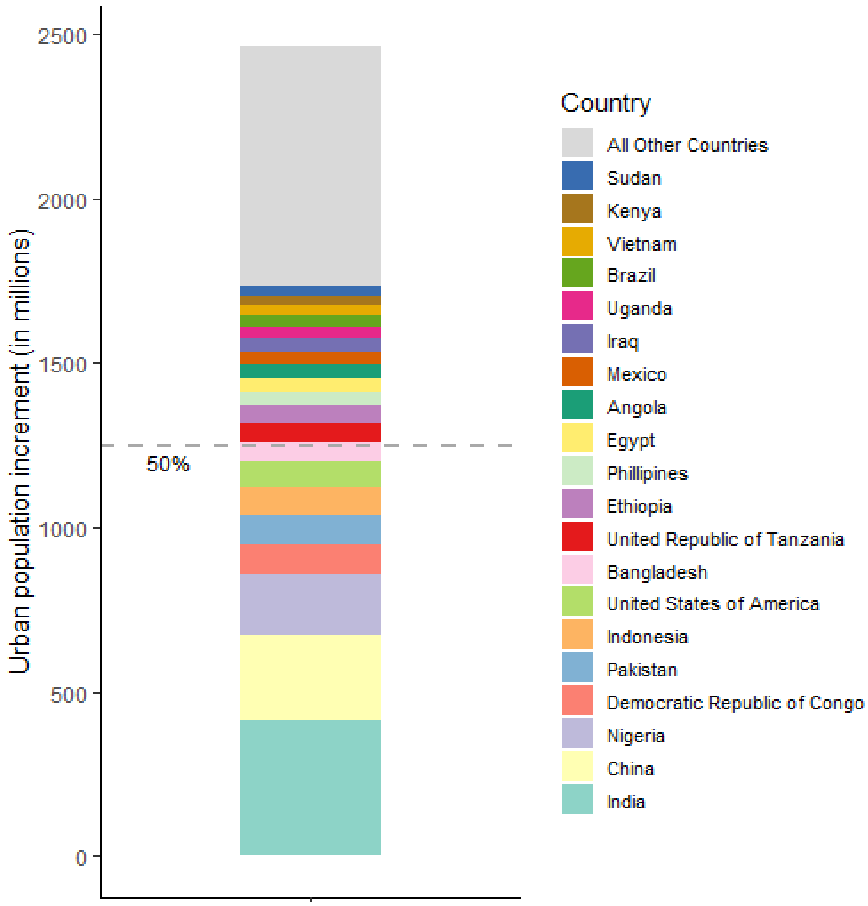
Supplementary figure 1 Projected increase in urban population between 2018 and 2050 by countries (Adapted from UN, DESA**).**



Supplementary table 1. Categorization of countries based on institutional scores across governance indicators (Rule of Law and Government Effectiveness)

Governance Indicator	Time-Period	Strong and Getting Stronger	Strong and Getting Weaker	Weak and Getting Stronger	Weak and Getting Weaker
		Mean > 2.5 **Difference = Positive**	**Mean > 2.5** **Difference = Negative**	**Mean <2.5** **Difference = Positive**	**Mean <2.5** **Difference = Negative**
Rule of Law	Pre-2000	**N America** (USA, Canada) **Oceania** (Australia) **Europe** (Austria, Finland, Netherlands, UK, Ireland, Germany, Uruguay) **EAP** (South Korea, Thailand) **India** **Middle East** (Jordan) **CS America** (Chile)	**Europe** (France, Spain, Portugal, Italy, Czech Rep, Hungary, Poland) **EAP** (Japan, Philippines) **Middle East** (Israel, UAE, Kuwait, Saudi Arabia) **CS America** (Argentina) **Africa** (Morocco)	**China** **CS America** (Brazil, Mexico, Peru) **Africa** (Zambia, Burkina, Faso, Ethiopia, Kenya, Algeria, Nigeria, Rwanda, Sudan) **EAP** (Vietnam) **Middle East** (Iran) **Europe** (Azerbaijan) **Rest Asia** (Turkey, Kazakhstan)	**Africa** (Egypt, Gambia, Ghana, Mali, Uganda, Zimbabwe, Sierra Leone) **Europe** (Romania, Armenia) **CS America** (Bolivia, Jamaica, Ecuador, Colombia, Venezuela, Russia) **EAP** (Indonesia) **Middle East** (Yemen)
	Post-2000	**N America** (USA, Canada), **Europe** (Finland, Sweden, Austria, Switzerland, Netherlands, UK, Germany, Ireland, France, Belgium, Czech Republic, Poland) **Oceania** (New Zealand, Australia) **EAP** (Hong Kong, Japan, Taiwan, South Korea, Malaysia) **Middle East** (Israel, Qatar, Jordan, Saudi Arabia) **CS America** (Chile, Uruguay)	**Europe** (Spain, Portugal, Hungary, Greece, Italy) **Middle East** (UAE, Kuwait) **CS America** (Puerto Rico, Costa Rica) **Africa** (South Africa, Ghana) **India**	**China** **Africa** (Tunisia, Senegal, Burkina Faso, Algeria, Ethiopia, Kenya, Togo, Cameroon, Nigeria, Liberia, Yemen, Ivory Coast, Guinea, Angola, Sudan, Congo) **Europe** (Romania, Bulgaria, Azerbaijan, Russia, Belarus) **CS America** (Panama, Brazil, Colombia, Peru, El Salvador, Dominican Republic, Cuba, Paraguay, Cambodia) **Rest Asia** (Georgia, Armenia, Kazakhstan, Pakistan, Bangladesh, Tajikistan, Uzbekistan) **Middle East** (Zambia, Iraq) **EAP** (Philippines, Indonesia, Myanmar)	**EAP** (Thailand) **Africa** (Egypt, Madagascar, Mali, United Republic of Tanzania, Libya, Guatemala, Mozambique) **CS America** (Argentina, Bolivia, Ecuador, Venezuela, Mexico) **Middle East** (Lebanon, Iran)
Governance Effectiveness	Pre-2000	**N America** (USA, Canada) **Oceania** (Australia) **Europe** (Austria, Finland, Netherlands, Germany, Spain, France, Hungary, Czech Rep) **EAP** (Japan, South Korea, Thailand) **Middle East** (Israel, UAE, Jordan) **CS America** (Mexico, Peru)	**Europe** (UK, Ireland, Portugal, Italy, Poland, Uruguay, **CS America** (Chile, Argentina, Jamaica, Peru,) **Middle East** (Kuwait)	**China** **Africa** (Morocco, Egypt, Gambia, Uganda, Burkina Faso, Algeria, Mali, Zambia, Rwanda, Ethiopia, Sierra Leone) **CS America** (Brazil, Ghana, Philippines, Colombia) **Rest Asia** (Turkey, Kazakhstan) **EAP** (Vietnam, Indonesia) **Middle East** (Iran)	**India** **Africa** (Zimbabwe, Kenya, Nigeria, Sudan) **CS America** (Bolivia, Ecuador) **Europe** (Romania, Armenia, Russia, Venezuela, Azerbaijan) **Middle East** (Saudi Arabia, Yemen)
	Post-2000	**China** **Europe** (Switzerland, Czech Republic, Poland, Bulgaria) **Oceania** (New Zealand) **EAP** (Hong Kong, Japan, Taiwan, South Korea, Malaysia, Thailand) **Middle East** (Israel, Qatar, UAE, Jordan) **CS America** (Chile, Uruguay, Costa Rica, Panama) **Rest Asia** (Georgia)	**N America** (USA, Canada), **Oceania** (Australia) **Europe** (Austria, Finland, Sweden, Netherlands, UK, Belgium, Germany, France, Ireland, Spain, Portugal, Hungary, Puerto Rico, Greece, Italy) **Africa** (South Africa, Tunisia) **CS America** (Mexico) **Middle East** (Kuwait)	**Africa** (Kenya, Algeria, Ethiopia, Angola, Liberia, Congo) **EAP** (Philippines, Indonesia, Vietnam) **CS America** (Colombia, El Salvador, Cuba, Dominican Republic, Ecuador, Cambodia, Paraguay **Middle East** (Saudi Arabia, Iran, Zambia, Iraq) **Rest Asia** (Armenia, Kazakhstan, Uzbekistan, Tajikistan) **Europe** (Romania, Russia, Azerbaijan, Belarus,	**India** **Africa** (Ghana, Senegal, Egypt, United Republic of Tanzania, Mozambique, Togo, Burkina Faso, Guatemala, Madagascar, Mali, Cameroon, Yemen, Nigeria, Guinea, Ivory Coast, Libya, Sudan) **CS America** (Brazil, Argentina, Peru, Bolivia, Venezuela) **EAP** (Myanmar) **Middle East** (Lebanon) **Rest Asia** (Pakistan, Bangladesh)

Supplementary table 2. Categorization of countries (from this study) in World Bank's (WB) income-based classification scheme

	Status of country in WB Classification 1987	Status of country in WB Classification 2014
Low-income countries	**China, India,** **Africa** (Burkina Faso, Ethiopia, Gambia, Ghana, Kenya, Mali, Nigeria, Rwanda, Sierra Leonne, Sudan, Uganda, Zambia) **CS America** (Colombia) **Others** (Indonesia, Vietnam, Yemen)	**Africa** (Burkina Faso, Congo, Ethiopia, Guinea, Liberia, Madagascar, Mali, Mozambique, Togo, Tanzania) **CS America** (Cambodia)
Lower middle-income countries	**Africa** (Egypt, Morocco, Zimbabwe) **CS America** (Bolivia, Chile, Ecuador, Jamaica, Mexico, Peru) **Europe** (Poland) **Others** (Jordan, Kazakhstan, Philippines, Thailand, Turkey)	**India,** **Africa** (Cameroon, Egypt, Ghana, Guatemala, Ivory Coast, Kenya, Nigeria, Senegal. Sudan, Zambia) **CS America** (Bolivia, El Salvador) **Others** (Armenia, Bangladesh, Georgia, Indonesia, Myanmar, Pakistan, Philippines, Tajikistan, Uzbekistan, Vietnam, , Yemen)
Upper middle-income countries	**CS America** (Argentina, Brazil, Venezuela) **Africa** (Algeria) **Europe** (Armenia, Azerbaijan, Czech Republic, Hungary, Portugal, Romania, Russia) **Others** (Iran)	**China,** **CS America** (Brazil, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Mexico, Panama, Paraguay, Peru) **Europe** (Azerbaijan, Belarus, Bulgaria, Romania) **Africa** (Algeria, Angola, Libya, South Africa, Tunisia) **Others** (Iran, Jordan, Kazakhstan, Lebanon, Malaysia, Thailand)
High-income countries	**N America** (USA, Canada), **Europe** (Austria, Denmark, Finland, France, Germany, Ireland, Netherlands, Spain, UK, Uruguay) **Others** (Australia, Israel, Japan, Kuwait, Saudi Arabia, South Korea, UAE)	**N America** (USA, Canada), **Europe** (Austria, Belgium, Czech Republic, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Portugal, Russia, Spain, Sweden, Switzerland, UK) **CS America** (Argentina, Chile, Puerto Rico, Uruguay, Venezuela) **Others** (Australia, Hong Kong SAR, Israel, Japan, Kuwait, New Zealand, Qatar, Saudi Arabia, South Korea, Taiwan, UAE)

Supplementary note 1

Theoretical foundations of the urban growth accounting regression analysis

We formulate a growth accounting model of urban land expansion, based on micro-foundations extracted from urban science and in particular urban scaling. Growth accounting is a tool developed by economists[1] to breakdown the growth of national GDP (a major economic indicator) into several components: the growth of capital investments, the growth in the labor market and technological change. Below, we develop a growth accounting equation emerging from urban scaling theory: our breakdown of the growth of urban land reflects two major factors in the theoretical framework: the growth in urban population and the growth of gross metropolitan product.

In urban scaling theory, urban features, Y_t, are hypothesized to follow power-law scaling of the form $Y_t = Y_0 N_t^{\beta}$ (Eq. 1) where Y_0 is a normalization constant, N_t is the population size at time, t, and β is the scaling exponent. The land area of cities is hypothesized to scale as $A_t = aN_t^{\alpha}$ (Eq. 2).

If the growth of GDP is governed by Eq. 1 and the growth of area is governed by Eq. 2, dividing (2) by (1) gives us:

$$\frac{A_t}{Y_t} = \frac{aN_t^{\alpha}}{Y_0 N_t^{\beta}} \qquad (3)$$

By multiplying with Y_t, the expression simplifies to:

$$A_t = \frac{a}{Y_0} N_t^{\alpha-\beta} Y_t \qquad (4)$$

With the above combination of scaling relationships, we can build a theoretical area-population-income scaling equation. We define income as GDP per capita, since in regression analysis, it is common to use a per capita measure of income).

We multiply and divide at the same time by N_t.

$$A_t = \frac{a}{Y_0} N_t^{\alpha-\beta} Y_t \frac{N_t}{N_t} \qquad (5)$$

Combining the N's on the numerator:

$$A_t = \frac{a}{Y_0} N_t^{1+\alpha-\beta} \frac{Y_t}{N_t} \qquad (6)$$

From the above equation it can be shown that:

$$\%\Delta A_t = (1 + \alpha - \beta)\%\Delta N_t + \%\Delta\left(\frac{Y_t}{N_t}\right) \qquad (7)$$

Given the standard assumptions in scaling theory regarding the values of α and β, in an econometric study estimating the above equation, we expect an estimated coefficient for population at 0.5 and for GDP/capita at 1. Further, given alternative assumptions (see below), the population coefficient can range from [0.25, 1] but the coefficient of GDP/capita should be expected at unity.

While this equation offers the predicted true value of coefficients that we would be extracting from examining a national system of cities, we can reorganize the resulting equation to denote the contribution of each (weighted) variable (population and GDP per capita) towards the expansion of urban areas.

So, the contribution of population would be $\frac{(1+\alpha-\beta)\ \%\Delta N_t}{\%\Delta A_t}$ while the contribution of GDP per capita would be $\frac{\%\Delta(Y_t/N_t)}{\%\Delta A_t}$.

Practically speaking, given specific theoretical assumptions about how populations mix, we expect that urban scaling laws would lead to parameter $(1 + \alpha - \beta)$ being equal to 0.5. So, for a specific urban area with $\%\Delta N_t = 1$, $\%\Delta(Y_t/N_t) = 3$, we would expect that $\%\Delta A_t = 3.5$. Which in turn means that the contribution of the rate of population growth (as a proportion of the rate of urban expansion) is 0.5/3.5=0.14 - about 14%. The contribution of the rate of GDP per capita (as a proportion to the rate of urban expansion) is 3/3.5=0.86 - about 86%.

In our analysis, we aggregate our results to regions which by definition are composed of several national systems of urban areas. Due to this fact, we are not testing the theoretical framework but using the structure it produces to justify our empirical estimation.

Note that the theoretical framework is constructed based on a single system of cities. Think about this as the U.S or Brazil or India (just to use national boundaries as something that defines a system). Our study is at global scale, so we combine information from multiple systems, even when we do the analysis for regions. So, in short, we are not directly testing the theory, but we are using the theory to justify running the statistical models that we do. Thus, assuming if different national systems of cities have differences in the way that urban populations mix, we expect different scaling relationships between urban characteristics (such as GDP and area) with population. So, by combining cities from multiple systems in a single empirical analysis (and missing portions of each system of cities by not including the full system), we cannot not directly test the theory. But the theory suggests that you can effectively conduct a growth accounting exercise due to the presence of scaling laws.

Supplementary note 2

Methodology: Regression relative importance; the uses of p-values and R-squared

Our main goal is to quantitatively identify the relative importance of two variables (population and GDP) towards urban expansion. Several definitions of variable relative importance have been proposed in the context of linear models. Definitions usually relate to relative importance of regressors towards prediction of the dependent variable or the role they play towards accounting for variance in the dependent variable, but there is no universally accepted definition[2]. Groemping[3,4] (2006, 2007) follows Achen[5] in distinguishing between "dispersion importance" methods (what is the relative contribution of regressors towards the explained variance); "level importance" methods (what is the relative attribution of a regressor towards the dependent variable mean); and "theoretical importance" (what is the marginal effect of a regressor with respect to the dependent variable in the model; this can be expressed in terms of statistical significance or magnitude significance of a regressor coefficient).

Various dispersion importance methods have been proposed in the literature. Few examples of these methods include dominance analysis, relative weights, commonality analysis. These techniques rely heavily on the R^2 goodness-of-fit statistic – rank ordering contributions of regressors to R^2 or partitioning R^2 in to unique and shared variance contributions[6]. Due to multicollinearity problems in regression analysis with a multiplicity of independent variables and biased coefficients, solutions have involved game theoretic methods and the use of the Shapely value imputation - an averaging of the sequential sum-of-squares over all orderings of regressors[7,8]. Feldman[9] proposes a covariance decomposition method approach (proportional marginal decomposition), taking advantage of connections between covariance decomposition and cooperative game theory. Dominance analysis (DA)[2,10] is based on the additive effect of each regressor in regression analysis. In this approach, predictors are compared in pairs for all possible regression specifications. The accuracy of DA has been criticised in the presence of sampling error variance and measurement unreliability[11].

We argue that a main weakness with the dispersion approach is the fact that commonly used goodness-of-fit statistics such as an R^2 can be spurious. Concerns have been raised about the way the R^2 statistic has been utilized in statistics – as a primary indicator for model fitting. The concerns span several decades[12] and point to the weakness of the indicator when interpreted as a goodness of fit measure, especially in the context of research designs that tries to maximize R^2 in search of a "best" model. In regression analysis, a well-known criticism of R^2 is that adding more predictor variables never reduces the value of the indicator; but this is easily addressed but a construct such as the adjusted R^2, correcting the statistic for the number of variables included in each model. The issues with all forms of the indicator though are deeper. More recently, through simulated data, Shalizi[13] shows that R^2 does not measure goodness of fit. For example, it can take small values when the model is correct and high values when the model is wrong. We adopt the perspective that neither R^2 or the adjusted R^2 is the only or even a particularly useful measure of how well a model fits; it should not be used as a yardstick for choosing "best" models. We do report the statistic as a method of comparison of our models to typical results in cross-sectional data analysis where models typically reach R^2 values in the 0.3 to 0.4 range. Since in our work we test an urban expansion accounting framework using distinct set of dummies as context for the models, we do not need directly compare goodness-of-fit between models.

An array of theoretical importance methods has also been discussed. Statistical significance testing in regression analysis has progressively lost some of its appeal due to the realization that distinguishing the effects of variables from zero is typically not a very good measure of the importance of a variable. Furthermore, statistical significance tests are not designed for comparisons between variables. Statistical significance has occupied a prominent spot in the field of statistical inference but in the last few decades it has increasingly been discussed under a more cautionary framing and the dangers of misuse, generating important statements regarding what scientists and researchers are not supposed to do[14–16]. For example, researchers have been warned to not base conclusions on the importance of different variable associations on any arbitrary level of statistical significance[17]. Or that we should not interpret p-value as "the probability that chance alone produced the observed association or effect or the probability that your test hypothesis is true". After several decades of warnings about the use and misuse of statistical significance, Wasserstein and Lazar[14] published the 'ASA Statement on p-Values and Statistical Significance' as a potential remedy to the problem plaguing many scientific fields. The result has been a sort of "statistics wars" according to some camps or a new era of statistics according to others. The developments in the field in the last few decades should be a prime example of the importance of correct interpretations of statistical indicators and more generally thoughtful evaluation of research results[14]. Furthermore, we are observing a renewed emphasis on magnitude significance[17] and the method we utilize in this paper is based on this magnitude of the estimated coefficients.

Having concerns about the use of "dispersion importance" methods and the reliance on the R^2 measure, we develop a novel method that addresses "level importance" and "theoretical importance" of our model variables supported by a theoretical urban expansion accounting framework to capture the relative contribution of population and economic growth. The method is reported in the main text or the article.

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