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The impact of strong activity disruption on building energetics

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1 **Abstract**

2 Evidence shows that biological organisms often exhibit sublinear (i.e., a scaling exponent $\alpha < 1$,
3 indicating that energy use increases less than proportionally with size) scaling of energy use with
4 size. These scaling patterns observed in biological organisms have also been observed in the
5 energy use of cities. However, at lower levels of organization where energetic interventions
6 can be more manageable, such as buildings, this analysis has remained more elusive due to
7 the difficulties in collecting fine-grained data. Here, we use the maintenance energy usage in
8 buildings at the Massachusetts Institute of Technology (MIT) from 2009 to 2024 to analyze
9 energetic trends at the scale of individual buildings and their sensitivity to strong external
10 perturbations. We find that energy use scales sublinearly with building volume, implying that
11 expected energy use per unit volume decreases with size. Because it has become debatable
12 how to better measure building performance, this scaling pattern naturally establishes a size-
13 dependent baseline, where deviations from the mean would imply relatively higher or lower
14 energy use compared to expectation. This size-dependent pattern became more pronounced
15 (i.e., more sublinear) until 2020. However, the strong activity disruption caused by the COVID-
16 19 pandemic acted as a major shock, removing this trend and leading to a return toward
17 earlier scaling behavior. This suggests that energetic patterns are contingent on relatively
18 stable conditions.

19 **Keywords:** energy, metabolism, scaling, change, society

20 Introduction

21 Efforts to address global warming have primarily focused on renewable energy innovation and
22 carbon pricing mechanisms [1, 2], while reducing building energy use has received less attention.
23 Yet, the building sector plays a crucial role in global energy use and carbon emissions, accounting
24 for 21% of global greenhouse gas (GHG) emissions (12 $GtCO_2$ -eq) and 31% of global final
25 energy demand (128.8 exajoules, EJ) in 2019 [3]. Notably, the global floor area of buildings in
26 cities is projected to increase from 244 billion m^2 in 2020 to 427 billion m^2 by 2050 [4]. This
27 means that the world is expected to add about 183 billion m^2 of new floor area to the global
28 building stock, the equivalent of adding two entire Boston cities every month for 30 years. It
29 becomes imperative then to understand the physical and socio-economic factors driving building
30 energetics for a sustainable future.

31 The study of energetics has a long tradition in the life sciences [5–7]. Evidence shows that bio-
32 logical organisms often exhibit sublinear (i.e., a scaling exponent $\alpha < 1$, indicating that energy
33 use increases less than proportionally with size) scaling of energy use with size—an observation
34 often discussed in relation to Kleiber’s Law [8]. Typically, the dependence of metabolism (y)
35 on body mass (x) takes the nonlinear form $y = \beta x^\alpha$, where β is a taxon-specific normalization
36 constant and α represents the scaling exponent [9]. For example, in the animal kingdom, the
37 scaling exponent is typically observed to be sublinear around $\alpha = 3/4$ [10]. This implies that
38 energy use increases less than proportionally with size, so energy use per unit size declines with
39 size. Put simply, while an elephant requires more energy than a mouse, the energy required per
40 unit mass is lower for the elephant. Interestingly, the scaling exponent seems to be different
41 across the tree of life. It has been shown that ordering organisms from relatively simple (e.g.,
42 prokaryotes) to relatively complex (e.g., metazoans), the scaling exponent changes from super-
43 linear ($\alpha > 1$) to sublinear ($\alpha < 1$) [10]. These scaling changes are expected to arise due to
44 body plan innovations filtered by natural selection [9–11].

45 The scaling patterns observed in biological organisms have also been observed in the energy use
46 of cities [12, 13]. Energy use linked to infrastructure tends to depend sublinearly on cities’ area,
47 and in contrast energy use linked to socio-economic factors tends to depend superlinearly on
48 cities’ area [12]. Importantly, it has been shown that such scaling exponents in cities can change
49 relatively fast [14], reflecting differences in the speed of change between biological and socio-
50 economic systems [15]. However, at lower levels of organization where energetic interventions
51 can be more manageable, such as buildings, this analysis has remained more elusive due to

52 the difficulties in collecting fine-grained data [16]. Indeed, a building as a physical individual
53 object does not undergo significant evolution, but a building as a human-made system has gone
54 through human selection since early settlement, from the makeshift tents in Stone Age (million
55 years ago- $\sim 10,000$ year ago) to the modern day architecture. Moreover, it remains unclear
56 the potential impact of strong activity disruptions on building energetics. To address this gap,
57 we use the maintenance energy usage in buildings at the Massachusetts Institute of Technology
58 (MIT) from 2009 to 2024 to analyze energetic trends at the scale of individual buildings [17].
59 This usage measurement includes both electricity and gas; information was not available for
60 energy use through materials. In particular, we investigate the relationship between energy use
61 and building size, the dynamics of the scaling exponents, and the impact of activity disruptions
62 caused by COVID-19. Lastly, we discuss the implications of our work for sustainable city design.

63 Results

64 Volume is a basic physical descriptor of buildings. As expected, studies have found a strong
65 association between building volume (area and height) and energy and gas usage [18, 19]. This
66 relationship is likely due in part to factors such as air-conditioning and heating demands driven
67 by exposure to environmental conditions. Similar to other buildings in cities, MIT buildings
68 have diverse usages, ranging from labs, offices, mixed, to residencies (Fig. 1a). Because we only
69 have information about floor area and maximum height, we estimate volume assuming buildings
70 are rectangular prisms. This assumption, while coarse, does not affect our conclusions as this
71 volume is fixed across years. MIT buildings range from relatively small ($3,552 \text{ m}^3$ equivalent to
72 1.42 Olympic Swimming Pools, building 51 Fig. 1a) to relatively large ($1,850,253 \text{ m}^3$ equivalent
73 to 1.85 Empire State Buildings, building 32 Fig. 1a), whereas the median volume is $183,918$
74 m^3 .

75 Focusing our analysis on the energetics of 86 buildings reported in 2024, we found that energy
76 use has a scaling relationship with volume defined by an exponent of $\alpha = 0.76$ (Fig. 2a) and
77 constant $\beta = 0.15$ (GJ per unit volume) (Fig. 2b). This indicates sublinear scaling, meaning
78 that energy use increases less than proportionally with volume and therefore that expected
79 energy use per unit volume decreases with building size. Because it has become debatable
80 how to better measure building performance [16], this scaling pattern naturally establishes a
81 size-dependent baseline for buildings, where deviations from the mean (i.e., positive or negative
82 regression residuals) would imply a building with relatively higher or lower energy use than
83 expected according to volume (Fig. 1a shows standardized residuals).

84 From 2009 to 2024, MIT (hosting almost 30,000 people [17]) had an average energy use in
 85 buildings of 2.6 PJ (a maximum of 2.88 PJ in 2011 and a minimum of 2.5 PJ in 2024). This
 86 usage is equivalent to 69,000 average U.S. households annually. However, changes in energy
 87 use across years were not proportional for every building. Figure 2a shows that the scaling
 88 exponent progressively decreased from $\alpha = 0.73$ in 2009 to $\alpha = 0.66$ in 2020, indicating more
 89 pronounced sublinearity over this period (i.e., a larger departure from linear scaling). We
 90 note that formal statistical tests comparing exponents across years were not the primary focus
 91 of this study; however, the observed temporal pattern is consistent across years and exceeds
 92 the uncertainty associated with individual regression estimates. In contrast, the normalization
 93 constant β progressively increased from $\beta = 0.46$ in 2009 to $\beta = 0.68$ in 2020, reflecting shifts
 94 in overall energy use intensity across buildings. In sum, these results show that changes in
 95 scaling behavior exhibited by MIT until 2020 were associated with differential energy use across
 96 building sizes.

97 However, the strong activity disruption caused by the COVID-19 pandemic led to a reversal to
 98 the mean from 2021-2024, bringing scaling patterns back toward earlier levels (Fig. 3a-b). The
 99 reversal to the mean effect implies that values far from the expectation in the present tend to
 100 be followed by values closer to the expectation in the future [20, 21]. To test this effect, we
 101 calculated the correlation between residuals in year 2009 (\mathbf{r}_0) and subsequent residuals (\mathbf{r}_t).
 102 This correlation implies the linear relationship $\mathbf{z}_t = \rho \cdot \mathbf{z}_0$, where $\mathbf{z}_t = \mathbf{r}_t \cdot \sigma_{\mathbf{r}_t}^{-1}$ (respectively,
 103 $\mathbf{z}_0 = \mathbf{r}_0 \cdot \sigma_{\mathbf{r}_0}^{-1}$) represents the vector of standardized residuals (Fig. 1a) and ρ corresponds to
 104 the Pearson correlation. The weaker the correlation (and statistically detectable), the stronger
 105 the reversal to the mean [20]. In line with this concept, Figure 3a shows that correlations
 106 were weaker from 2021-2023. Additionally, the reversal to the mean effect requires that the
 107 conditional expected value of observations in the future are bounded by the conditional expected
 108 value of observations in the present [21]. Using again standardized residuals as observations,
 109 the previous statement formally implies $\mu = 0 \leq E[\mathbf{z}_t | \mathbf{z}_0 > h] < E[\mathbf{z}_0 | \mathbf{z}_0 > h]$ and $\mu =$
 110 $0 \geq E[\mathbf{z}_t | \mathbf{z}_0 < h] > E[\mathbf{z}_0 | \mathbf{z}_0 < h]$, where h is a standardized threshold value (interpreted as
 111 standard deviations). Figure 3b shows the strongest reversal to the mean ($\mu = 0$) within the
 112 period 2021-2024 across different threshold values.

113 Discussion

114 The findings of this study reveal a distinct scaling relationship between building energy use
 115 and volume, mirroring patterns observed in biological metabolism [9, 12]. This discovery is

116 qualitatively consistent with metabolic scaling relationships observed in some biological systems.
117 Specifically, the energy use of buildings follows a sublinear scaling as a function of size, indicating
118 that larger buildings tend to have lower energy use per unit volume compared to smaller ones.
119 While we did not have information about people in each building (due to the complexity in the
120 day-to-day dynamics at MIT), it is expected that the number of people will grow proportionally
121 to building size. Notably, the decrease in energy use per unit volume in larger buildings likely
122 stems from structural and operational factors, such as centralized circulation systems (less
123 energy dissipation) and economies of scale in energy distribution. Future work should further
124 investigate the extent to which human-made systems can indeed have similar scaling patterns
125 as biological organisms [12].

126 Over the years preceding 2020, sublinearity became more pronounced, reflecting changes in the
127 scaling relationship over time. However, the strong activity disruptions caused by the COVID-19
128 pandemic abruptly altered this trajectory, leading to a return toward earlier scaling levels (Fig.
129 2b). This alteration may reflect the disruption of operational practices that previously reduced
130 energy waste over the years. The rapid shift in energy-use trends highlights the sensitivity of
131 building energetics to external shocks. This pattern suggests that, while reductions in energy use
132 per unit volume can be achieved through sustainability-driven targets, they remain contingent
133 on stable usage patterns and operational management strategies [22]. In general, this resonates
134 with biological changes that tend to occur during periods of relatively stable environments
135 [10, 11]. Yet, under strong perturbations, energetic processes may return to the expectations
136 set by first principles.

137 These insights carry significant implications for sustainable building design and energy policy. If
138 larger buildings naturally exhibit lower energy use per unit volume, then urban planning could
139 expand the construction of high-volume structures to increase energy performance and reduce
140 floor area. This may also help in reducing land-use changes with lower ecological impact. Yet,
141 in absolute terms, larger buildings can require excessive energy flows that may not be met in
142 specific areas or may rely too heavily on fossil fuels. Therefore, optimization processes can take
143 into account energy use, absolute usage, area, carbon footprint, and number of people served or
144 affected. Moreover, future policies should acknowledge that energy performance may be fragile
145 to external disruptions and promote sustainable practices in both new and existing buildings to
146 ensure sustained performance. This can be achieved by implementing adaptive energy systems,
147 such as smart grid integration [23], which help buildings dynamically respond to fluctuations
148 and sustain performance even during unexpected challenges.

149 Despite several guidelines being proposed, this study presents certain limitations that warrant
150 further exploration. The analysis is confined to a single institution, and while MIT provides a
151 rich dataset due to its diverse building types and functions, expanding this research to other
152 universities or urban environments would help validate the applicability of these findings. Ad-
153 ditionally, the study does not account for energy usage variations within individual buildings,
154 such as differences in energy use patterns among laboratories, offices, residential halls, and
155 mixed-use buildings, or for building shape and internal architecture. Future research should
156 incorporate finer-grained data, such as number of people, to better understand the micro-level
157 determinants of energy use within buildings. Understanding these dynamics provides valuable
158 guidelines for designing more resilient and energy-efficient buildings, particularly in the context
159 of global sustainability challenges. Continued investigations should focus on delving deeper into
160 the underlying mechanisms of energy scaling, enabling more effective policies and innovations
161 in building energy management.

162 **Abbreviations**

163 MIT: Massachusetts Institute of Technology

164 GHG: greenhouse gas

165 US: United States

166 **Declarations**

167 **Ethics approval and consent to participate** This study does not incorporate any personal
168 information.

169 **Consent for publication.** All of the authors consent to publication.

170 **Availability of data and material:** The code and data associated with this work can be
171 accessed at <https://github.com/hsuanmina/building-energetics>. The code and data will
172 be deposited at Zenodo upon acceptance.

173 **Competing interests.** The authors declare no competing interests.

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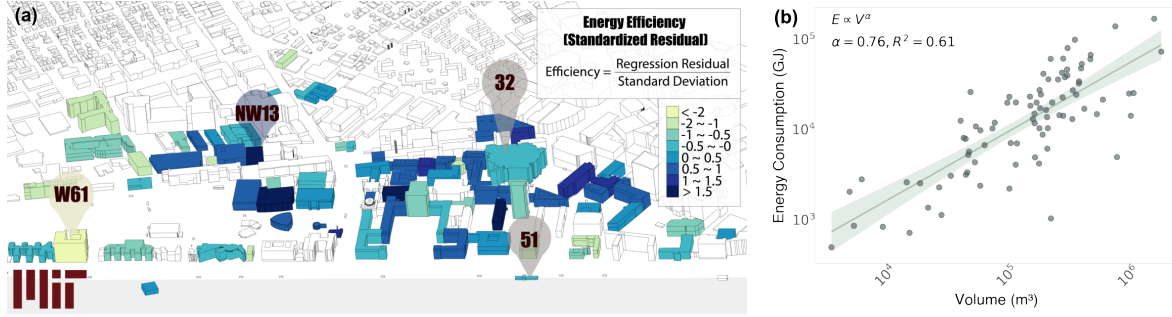


Figure 1: **Building energetics at MIT in 2024.** (a) Map of MIT buildings illustrating the volume range. Buildings 32 and 51 are shaded in gray representing the largest and smallest, respectively. The lighter the color, the lower the energy use per unit volume. Buildings in the lightest and darkest two shades are specifically highlighted to represent the extremes of standardized residuals (among the buildings analyzed, Building W61 demonstrates the highest standardized residual, while Building NW13 exhibits the lowest standardized residual). Formally, size-adjusted energy use is measured by standardized residuals ($\mathbf{z} = \mathbf{r} \cdot \sigma_{\mathbf{r}}^{-1}$, see main text), considering that the expectation is given by the scaling relationship $\text{energy} \propto \text{volume}^{\alpha=0.76}$. This scaling relationship is similar to the one exhibited by biological organisms. (b) Scaling relationship between energy use and volume. Each point corresponds to 1 out of 86 different buildings, the line represents the expectation (used in panel a to calculate standardized residuals), and the shaded area corresponds to the 95% confidence interval (also used in panel a to calculate standardized residuals).

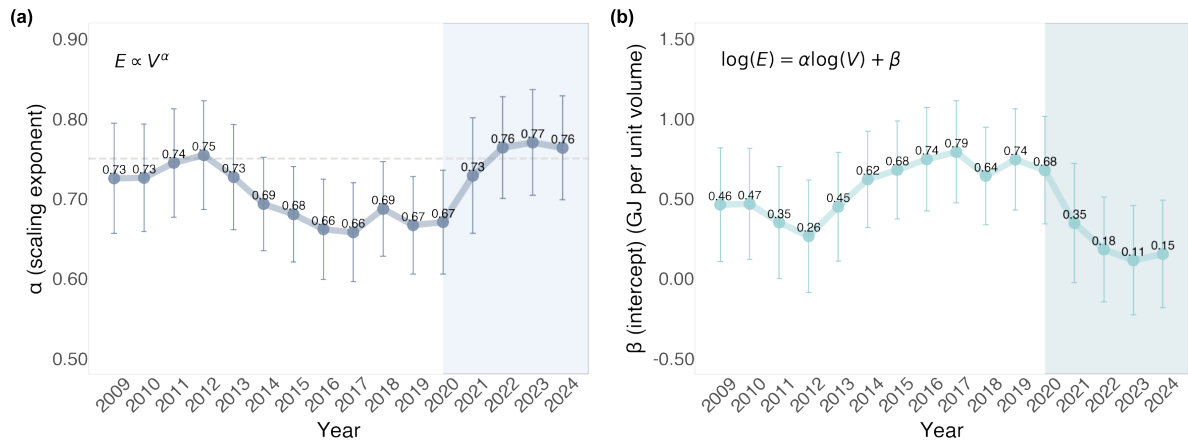


Figure 2: **Building energetics at MIT before and after the COVID-19 pandemic.** (a) The scaling exponent (α) defining the dependence of energy use on volume changed across years. At the beginning of the time series, the scaling exponent is on average close to $\alpha = 0.75$. This scaling exponent decreased to $\alpha = 0.66$ before 2020. However, during the period after COVID-19 (shaded area), the scaling exponent returned toward earlier levels ($\alpha = 0.75$). (b) The normalization constant (β) defining the energy use per unit volume changed across years, reflecting that smaller buildings started to demand more energy.

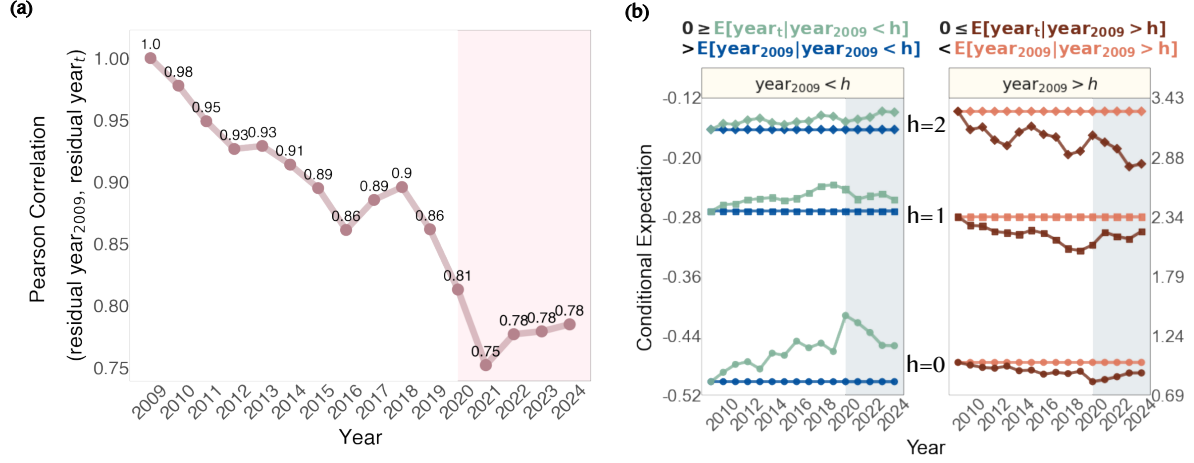


Figure 3: **Reversal to the mean.** (a) Pearson correlation (ρ) between residuals in year 2009 and year t ($\mathbf{z}_t = \rho \cdot \mathbf{z}_{2009}$). (b) Conditional expected value of observations in the year t ($E[\mathbf{z}_t | \mathbf{z}_{2009} > h]$ and $E[\mathbf{z}_t | \mathbf{z}_{2009} < h]$) are bounded by the conditional expected value of observations in year 2009 ($E[\mathbf{z}_{2009} | \mathbf{z}_{2009} > h]$ and $E[\mathbf{z}_{2009} | \mathbf{z}_{2009} < h]$), where h is a standardized threshold value. The weaker the correlation and the closer to the mean ($\mu = 0$), the greater the reversal to the mean (shaded areas).

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