ARTICLE IN PRESS

Cities xxx (xxxx) xxx

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Low vs. high income: The impact of high-rise buildings on prevalence of obesity

Yuval Arbel [a,*], Yifat Arbel [b], Amichai Kerner [c], Miryam Kerner [d,e]

[a] Sir Harry Solomon School of Economics and Management, Western Galilee College, Acre 2412101, Israel
[b] Department of Mathematics, Bar Ilan University, Ramat Gan, Israel
[c] School of Real Estate, Netanya Academic College, Netanya 4223587, Israel
[d] The Ruth and Bruce Rapoport Faculty of Medicine, Technion – Israel Institute of Technology, Haifa 3523422, Israel
[e] Department of Dermatology, HaEmek Medical Center, Afula 1834111, Israel

ARTICLE INFO

Keywords:
High-rise buildings
Obesity
Externalities
Inequality
Low income quantile

ABSTRACT

The relationship between health, proxied by the prevalence of obesity, and the level of income is well documented. Based on the CDC report at a US statewide level between 2011 and 2020, the current study extends this discussion by exploring the impact of urban environments, proxied by the number of skyscrapers, on this relationship. In this context, the question that still remains open is what is the extent of urban development that can reduce the dimensions of the obesity pandemic to a minimum and whether this effect is different across poor versus rich populations. Consequently, the contribution of this study is the use of the quadratic model, which permit non-monotonic relationships between obesity prevalence and the number of skyscrapers. We also examine the incremental change in the number of skyscrapers. The global aspect of our study may be described as follows. For countries with per-capita GDP higher than $75,000 (lower than $25,000) – urban development of skyscrapers is expected to be beneficial on obesity prevalence up to 142 (126) skyscrapers. Compared to poor countries, the incremental impact of high-rise construction on obesity prevalence at the downward domain of the U-shaped curve is expected to be much more beneficial among rich countries.

1. Introduction

Income inequality has profound consequences in terms of health (including obesity, diseases and life expectancy), employment and achievements in life. Woolf et al. (2015) suggest that if race is controlled, income is found to be a more important characteristic than race.[1] In their review, Cooper and Stewart (2021) argue that a large portion of the worse outcomes of low-income households emanates from lack of financial resources rather than other reasons. Morrish and Medina-Lara (2021) found evidence for endogenous relationships between unemployment and loneliness. On the one hand, higher levels of loneliness were observed following job loss. On the other hand, loneliness was found to be predictive of unemployment. Tapia-Muñoz et al. (2022) found association of greater country-level income inequality with higher prevalence of loneliness over and above individual-level sociodemographic characteristics among older population in USA and European countries.

There is an abundance of evidence suggesting that compared to the richest population, the poorest population achieve lower outcomes. Cooper and Stewart (2021) review academic studies that investigated the outcomes of children in terms of cognitive ability, educational achievements, school attainment, social-behavior, health, parenting/home environment or maternal mental health in EU and OECD countries. The authors provide a strong evidence base, which indicates that a

* Corresponding author.
E-mail addresses: YuvalAr@wgalil.ac.il (Y. Arbel), kerneram@netvision.net.il (A. Kerner), Kerneram@technion.ac.il (M. Kerner).

[1] Referring specifically to health, according to Woolf et al. (2015) People with lower income levels in the United States report poorer health and have a higher risk of disease. In Woolf et al. (2015): Figure 1, for example – 22.8 % of adults whose income is below $35,000 per annum self-report of Fair or Poor Health. By contrast, only 5.6 % of adults whose income is above $100,000 per annum self-report of fair or poor health. Referring to higher risk of disease or illness – Woolf et al. (2015) report on 11 % prevalence of diabetes among adults whose income is below $35,000 per annum, compared to only 5.9 % among adults whose income is above $100,000 per annum. Moreover, in terms of risk of disease – compared to race, income is considered a stronger characteristic. Higher – income blacks, Hispanics, and Native Americans have better health than members of their groups with less income, and this income gradient appears to be more strongly tied to health than their race or ethnicity (Woolf et al., 2015, p. 1).

https://doi.org/10.1016/j.cities.2023.104697
Received 24 October 2023; Received in revised form 16 November 2023; Accepted 23 November 2023

large portion of the worse outcomes of low-income households comes from money itself rather than the correlations of poverty with other household and parental characteristics (page 1000). Those may include the lack in the emotional resources needed for supportive and nurturing parenting behaviors due to financial pressures oppressing the parents (pages 982).

Manstead (2018) argues that the material circumstances in which people develop and live their lives have a profound influence on the ways in which they interpret themselves and their social environments. The resulting self-perception differences between working-class and middle- and upper-class making it harder for working-class individuals to benefit from the kinds of educational and employment opportunities that would increase social mobility and thereby improve their material circumstances. In this context, Arbel et al. (2022) demonstrate the negative relationship between obesity and the self-evaluation of property values in Israel. Given that obesity is negatively correlated with income, this outcome may suggest a higher self confidence among the upper class.

In the context of income inequality, high-rise buildings and urban environments, Panczak et al. (2013) compared the ground and eight floor in high rise buildings in Switzerland. The authors found lower risk of mortality from all causes, from respiratory diseases, from cardiovascular diseases and from lung cancer among the eight floor residents. No association was found between the floor and mortality resulting from suicide. A possible explanation is that the floor of residence captures residual socioeconomic stratification and is likely to be mediated by behavioral (e.g. physical activity), and environmental exposures (access to a method of suicide).

The literature suggests that high-rises are less satisfactory than other housing forms for most people, that they are not optimal for children, that social relations are more impersonal and helping behavior is less than in other housing forms, that crime and fear of crime are greater, and that they may independently account for some suicides (Gifford, 2007).

While previous studies examined the risks of high-rise building construction, less attention has been paid to the diverse impacts of high-rise buildings on their occupants. Based on the qualitative research of high-rise residential buildings of District 22 of Tehran, the most significant and influential impacts identified by this study were anti-social behavior, lack of social cohesion, and lack of social contact with neighbors (Dwijendra et al., 2021).

The objective of the current study is to examine the impact of the urban environment, proxied by the number of skyscrapers, on obesity prevalence based on stratification of income by categories. The study is based on information obtained from the CDC regarding obesity prevalence in 48 US States. Data were extracted by combining the separate files to 2011–2020. Each income category is uniformly distributed across US states (see Appendix A1).

Results of this study support a U-shaped curve for the two most extreme population groups stratified by income levels: the poorest (below $25,000 per annum) and the richest (above $ 75,000 per annum). Yet, regardless of the number of skyscrapers, the *maximum* projected obesity prevalence among the richest (28 % of the respective population) is lower than the *minimum* projected obesity prevalence among the poorest (31 % of the respective population). Finally, the incremental change for an additional skyscraper is steeper among the richest.

The following interpretation may be given to the obtained outcomes. Rich people have more time to use infrastructure up to a certain amount of skyscrapers. Beyond that – the mixing of uses in the same building – makes it possible to shop without leaving the perimeter of the building.

Appendices A2–A3 show the stratification of countries based on per-capita GDP (a proxy for the personal level of income). The global aspect of our study may be described as follows. For countries with per-capita GDP higher than $75,000 (lower than $25,000) – urban development of skyscrapers is expected to be beneficial on obesity prevalence up to 142 (126) skyscrapers.

The U-shaped curve for the poor US States is flatter than the rich states. Consequently, at a global level, compared to poor countries, the incremental impact of high-rise construction on obesity prevalence at the downward domain of the U-shaped curve is expected to be much more beneficial among rich countries.

The novelty of this research lies in three contributions:

1) The investigation of the income ladder in the context of obesity and the urban vs rural environments, proxied by the number of skyscrapers in the state.
2) The use of a quadratic functional form, which relaxes the restriction of a monotonic decline or increase and permits a non-monotonic change if such a change is supported by the data.
3) The analysis of incremental changes in obesity prevalence with the number of skyscrapers separately for the population belonging to the highest and lowest income quantiles.

In sum, the world is going toward the direction of dense urban construction in light of the increase in world population. Obesity is a global pandemic associated with considerable costs and increased mortality rates. There is a growing willingness among public policy planners to reduce the dimensions of this pandemic.

The connection between high-rise buildings and obesity is one of the most important issues, because in the coming years most people in the world are expected to live in skyscrapers. In 2011, half of the world's population lives in dense cities. The cities today are richer, healthier and the living conditions in them are more enticing (Glaeser, 2011, p. 1). The question that still remains open is what is the extent of urban development that can help reduce the dimensions of the obesity pandemic to a minimum and whether this effect is different across poor versus rich populations. To the best of our knowledge, this question has not yet been discussed in the literature.

The remainder of this article is organized as follows. Section 2 provides the description of data employed in this study and describes the empirical model estimated via regression analysis and Section 3 – depicts the regression outcomes. Finally, Section 4 concludes and summarizes.

2. Methodology and descriptive statistics

Consider the following interaction model consisting of the subsequent structural equation:

$$Obesity\_Prevalence = a_1^{'}(Year - 2011) + a_1 Skyscrapers^2 + a_2 Income \times Skyscrapers^2 + b_1 Skyscrapers + b_2 Income \times Skyscrapers + c_1 + \mu_1 \quad (1)$$

where *Obesity_Prevalence* in the US state is the dependent variable, $Year(=2011, 2012, \cdots, 2020)$, $Skyscrapers^2 = Skyscraper \times Skyscraper$ (the squared number of skyscrapers in the US state), *Skyscraper* and *Income* (*Income* $= 1$ for the highest income quantile with above $75,000 per annum and 0 for the lowest income quantile with below $25,000 per annum) are the independent variables, $a_1^{'}, a_1, a_2, b_1, b_2, c_1, c_2$ are the parameters and μ_1 is the classical random disturbance term.

According to Chiang & Wainwright, 2005: 229–231, the general form of the quadratic function is: $y = ax^2 + bx + c$ $(a \neq 0)$ with a second derivative equals to $2a$. Given that this derivative will always have the same algebraic sign of the coefficient a, a U-shaped curve with a global minimum at $(\frac{-b}{2a}, \frac{-b^2+4ac}{4a})$ is obtained if $a > 0$, and an inverted a U-shaped curve with a, the global maximum at $(\frac{-b}{2a}, \frac{-b^2+4ac}{4a})$ is obtained if $a < 0$.

Given that the most extreme differences in terms of obesity prevalence are obtained for the lowest and highest income categories, we focus only on these two categories. This is demonstrated in Appendices A4–A5. The figure in Appendix A4 reports the average percent of the US

Table 1
Pearson correlation matrix.

	Obesity prevalence
A. Between $75,000 or greater and lower categories	
$75,000 or greater	−0.4115*** (<0.01)
N=	2784
B. Between less than $15,000 and higher categories	
$75,000 or greater	0.2824*** (<0.01)
N=	2784
C. Between $75,000 or greater and less than $15,000	
$75,000 or greater	0.6549*** (<0.01)
	928
Less than $15,000	−0.6549*** (<0.01)
N=	928

Notes: Numbers in parentheses are *p*-values for the rejection of the null hypothesis of zero correlation.
*** $p < 0.01$.

obese population ($BMI \geq 30$) stratified by income levels. As can be seen from the figure, the percentage of obese population steadily *drops* with annual income. 34.9112 % of the US population whose annual income is below $15,000 is considered obese, compared to only 26.7194 % among the population whose annual income is above $75,000 – a gap of 8.1918 %. Column (2) in Appendix A4 demonstrates that this difference is statistically significant at the 1 % level.

Finally, Table 1 provides the correlation matrix between the prevalence of obesity and different income categories. The Table is divided into three panels. Panel A gives the correlation between the highest income category (above $75,000) and lower income categories (below $75,000). Panel B exhibits the correlation between the lowest income category (below $15,000) and higher income categories (above $15,000). Panel C gives the correlation between the highest income category (above $75,000) and the lowest income category (below $15,000).[2] The Pearson correlation matrix reaffirm the negative relationship between obesity prevalence among the highest income category of above $75,000 and the categories below $75,000 (Pearson correlation between −0.6549 and −0.4115) and the positive relationship between obesity prevalence among the lowest income category of below $15,000 and the categories above $15,000 (Pearson correlation between +0.2824 and +0.6549).

3. Results

Table 2 reports the outcomes of the regression analysis obtained from the empirical model. In columns 1 (2) robust (non-robust) *p*-values are given in parentheses At the middle of the table, the R^2 and the outcomes of the regression significance test, Ramsey's RESET (Regression Specification Error Test – see Ramanathan, 2002: 270–271) procedure are displayed.[3]

In both columns, the null hypothesis stating that none of the explanatory variables explain the dependent variable is clearly rejected at the 1 % level ($p(6,921) = 2.8305 \times 10^{-162} - 8.484 \times 10^{-162}$). The R^2 exhibits an explanatory power of 56 % – the independent variables explain 56 % of the variance of the dependent variable. Referring to the non-robust column, the RESET procedure supports the conclusion of correct specification of the empirical model at the 1 % level ($p(3,918) = 0.0103$).

Referring to the coefficients of the independent variables in Table 2, results demonstrate an average increase in obesity prevalence of 0.623 % per annum during 2011–2020. This is an indication of the obesity pandemic. Referring to the bottom part of Table 2 and the top part of Fig. 1, for both populations, namely, income variable of above $ 75,000 (the richer) and below $ 25,000 per annum (the poorer), a U-shaped curve with the number of skyscrapers is obtained. However and regardless of the number of skyscrapers, the curve of the group of above $ 75,000 is lower, indicating reduced levels of projected obesity

Table 2
Regression analysis.

	(1)	(2)
Standard errors	Robust	Non-robust
Variables	Obesity prevalence	Obesity prevalence
(Year-2011)	0.623***	0.623***
	(>0.01)	(>0.01)
Income	−7.683***	−7.683***
	(>0.01)	(>0.01)
Skyscrapers	−0.0694***	−0.0694***
	(1.22×10^{-5})	(3.15×10^{-7})
Income × Skyscrapers	−0.0522**	−0.0522***
	(0.0155)	(0.00628)
Skyscrapers × Skyscrapers	0.000275***	0.000275***
	(5.23×10^{-6})	(7.23×10^{-7})
Income × Skyscrapers × Skyscrapers	0.000153*	0.000153*
	(0.0612)	(0.0504)
Constant	32.61***	32.61***
	(>0.01)	(>0.01)
Observations	928	928
R-squared	0.564	0.564
F-value (regression significance)		
F (6, 921)=	198.04	198.88
P(6,921)=	8.484×10^{-162}	2.8305×10^{-162}
Ramsey's RESET procedure		
F(3, 918)=	5.28	3.78
p(3, 918)=	0.0013	0.0103
Minimum points of obesity prevalence		
Annual income below $25,000		
Skyscrapers $= -b_1/2a_1$	126 [114, 138]	126 [114, 138]
Projected prevalence of obesity $= \frac{-b_1^2 + 4a_1c_1}{4a_1}$	31 [29, 33]	31 [29, 33]
Annual income above $75,000		
Skyscrapers $= -(b_1 + b_2)/2(a_1 + a_2)$	142 [137, 147]	142 [137, 147]
projected prevalence of obesity $= \frac{-(b_1 + b_2)^2 + 4(a_1 + a_2)(c_1 + c_2)}{4(a_1 + a_2)}$	19 [18, 21]	19 [18, 21]

Notes: The Income variable receives 1 for annual income of above $75,000 and zero for below $25,000 in the state. The Ramsey's RESET (Regression Specification Error Test – see Ramanathan, 2002: 270–271) procedure is based on two steps. The first step of the procedure is the construction of vector of predictions ($\hat{Y}$) from the model given in Eq. (1). The second step is the incorporation of $\hat{Y}^2$, $\hat{Y}^3$ and $\hat{Y}^4$ in Eq. (1) as additional independent variables and testing the joint null hypothesis that their coefficients equal zero. If the null hypothesis is not rejected, one could argue that the model specification is appropriate. According to this procedure, the null hypothesis is not rejected for the non-robust standard errors. Robust (non-robust) *p*-values are given in parentheses in column (1) (column (2)).
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

[2] For the states-years stratification of observations based on income categories – see Appendix A1.

[3] The procedure is based on the following model: $Obesity\_Prevalence = a_1''(Year - 2011) + a_2''Skyscrapers^2 + a_3''Income \times Skyscrapers^2 + b_1''Skyscrapers + b_2''Income \times Skyscrapers + b_3''Income + c_2'' + d_2''\hat{Y}^2 + d_3''\hat{Y}^3 + d_4''\hat{Y}^4 + \mu_2''$ where $\hat{Y}$ is the vector of projected values obtained from Eq. (1). This unrestricted model contains 10 explanatory variables, including the constant term. The WALD statistical procedure is designed to test whether $d_2'' = d_3'' = d_4'' = 0$ on a sample of 928 observations. Consequently, Eq. (1) is the restricted model. The calculated F-statistics has 3 degrees of freedom in the numerator and 918 in the denominator.

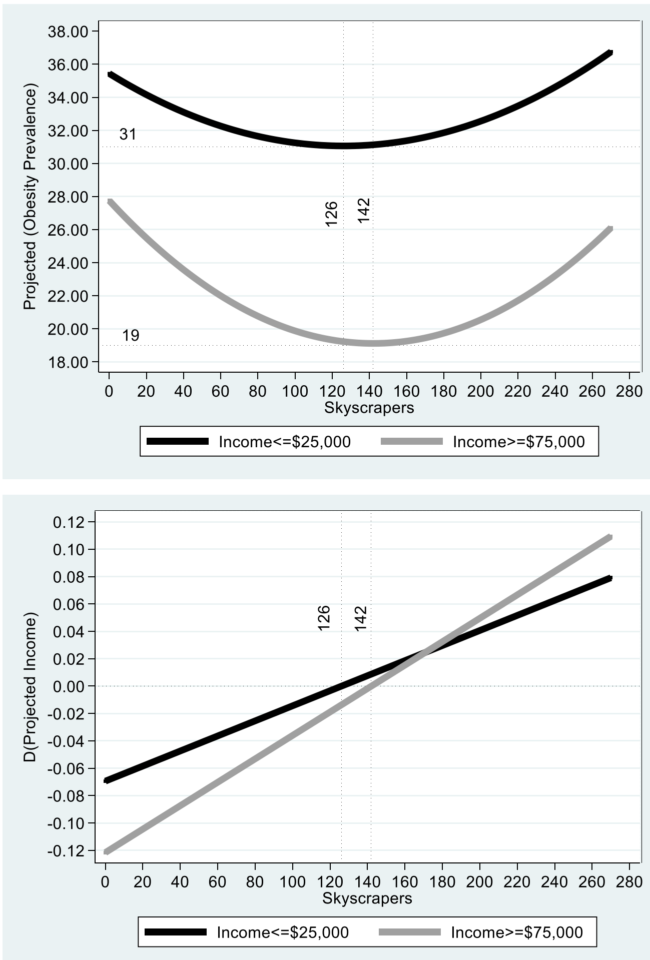


Fig. 1. Impact of skyscrapers on the prevalence of obesity: Low vs. high income. Notes: The graphs are based on the outcomes reported on Table 2. The Income variable receives 1 for annual income of above $75,000 and zero for below $25,000 in the state.

prevalence among the richer group. Even the minimum projected obesity prevalence among the poorer – 31 % – is higher than the maximum projected obesity prevalence among the richer – approximately 28 %.

The bottom part of Fig. 1 gives the first derivative of the top part among the two groups. The implication is a higher pace of change in the projected obesity prevalence among the richer group with one additional skyscraper. The first skyscraper has a much more beneficial impact on the richer group – 0.12 percent decrease in projected obesity prevalence compared to the poorer group – only 0.07 percent decrease. Yet, this advantage is offset by an increase in the number of skyscrapers. When the number of skyscrapers reach 126 for the poorer and 142 for the richer, the accumulated number of skyscrapers overturns from an asset – contributing to a projected beneficial decrease in projected obesity prevalence – to a liability – contributing to a projected damaged increase in projected obesity prevalence.

4. Summary and conclusions

Based on information on 48 US States, the objective of the current study is to examine the impact of the urban environment, proxied by the number of skyscrapers, on obesity prevalence based on stratification of income by quantiles.

Results of this study support a U-shaped curve for the two most extreme population groups stratified by income levels: the poorest (below $25,000 per annum) and the richest (above $ 75,000 per annum). Yet, regardless of the number of skyscrapers, the maximum projected obesity prevalence among the richest (28 % of the respective population) is lower than the minimum projected obesity prevalence among the poorest (31 % of the respective population). The implication is that compared to poor population, rich population exhibit much better outcomes. This result is supported empirically by both non quality-adjusted comparison across US States (8.918 % difference of obesity prevalence between the poorest and the richest in favor of the richest) and in many quantitative and qualitative studies (e.g., Woolf et al., 2015; Manstead, 2018; Cooper & Stewart, 2021).

A unique aspect of this study is the examination of the potential U-shape curve and the incremental change for an additional skyscraper among the two extreme groups in the income ladder. While for both groups the U-shaped curve is supported empirically, the curve among the poorest is much flatter. The U-shaped curve may be interpreted as congestion effect of structures. At the initial phase, the accumulation of high-rise buildings has a beneficial impact on the prevalence of obesity. With the development of the urban environment, this impact is reversed as the streets become crowder and more food intake opportunities arise in the proximity of the high-rise buildings. Rich people may use the urban infrastructure more efficiently up to a certain amount of skyscrapers. Beyond that – the mixing of uses in the same building – makes it possible to shop more efficiently without leaving the perimeter of the building.

Research findings may be of assistance to city developers and public policy planners. They clearly support the limitation of the number of skyscrapers up to a certain point, where health advantages in terms of obesity prevalence are exhausted. To support this conclusion further, additional research is required at a lower grid.

In sum, the world is going toward the direction of dense urban construction in light of the increase in world population. Obesity is a global pandemic associated with considerable costs and increased mortality rates. There is a growing willingness among public policy planners to reduce the dimensions of this pandemic.

The connection between high-rise buildings and obesity is one of the most important issues, because in the coming years most people in the world are expected to live in skyscrapers. In 2011, half of the world's population lives in dense cities. The cities today are richer, healthier and the living conditions in them are more enticing (Glaeser, 2011, p. 1). The question that still remains open is what is the extent of urban development that can help reduce the dimensions of the obesity pandemic to a minimum and whether this effect is different across poor versus rich populations. To the best of our knowledge, this question has not yet been discussed in the literature.

City and public policy planners should also account for health considerations (obesity prevalence), including:

1) Outlining an urban policy to reduce the complications that arise as a result of obesity and adapting them to the level of income per capita and the number of skyscrapers in the city.
2) Creating an international urban index that will consider the number of skyscrapers, the prevalence of obesity and the income per capita. The index will reflect the common risk of obesity in that city.
3) Allowing city planners and architects to use common urban tools, such as air rights or consolidating lots for higher buildings to reduce the incidence of obesity in that city.
4) Under the same conditions of urban development proxied by the number of skyscrapers, obesity prevalence among high-income countries is expected to be much lower than those obtained in poor countries.

The global aspect of our study may be described as follows. For countries with per-capita GDP higher than $75,000 (lower than $25,000) – urban development of skyscrapers is expected to be beneficial on obesity prevalence up to 142 (126) skyscrapers.

The U-shaped curve for the poor US States is flatter than the rich states. Consequently, at a global level, compared to poor countries, the incremental impact of high-rise construction on obesity prevalence at the downward domain of the U-shaped curve is expected to be much more beneficial among rich countries.

Ethics approval and consent to participate

This research does not require IRB approval since it does not involve any experiment or manipulation of subjects. All authors read and approved the final manuscript for submission.

Consent for publication

Non-applicable.

Funding

None of the authors receive any direct or indirect funding for this manuscript.

CRediT authorship contribution statement

Yuval Arbel contributed to the study conception and design, data collection and analysis, the first draft and comments on previous versions of the manuscript.

Yifat Arbel contributed to the study conception and design, data collection and analysis, the first draft and comments on previous versions of the manuscript.

Amichai Kerner contributed to the study conception and design, data collection and analysis, the first draft and comments on previous versions of the manuscript.

Miryam Kerner contributed to the study conception and design, data collection and analysis, the first draft and comments on previous versions of the manuscript.

Declaration of competing interest

None of the authors have potential conflicts of interest, financially or non-financially, directly, or indirectly related to this work.

Availability of data and materials

The datasets used and/or analyzed during the current study is available on the following link: Center for Disease Control and Prevention (CDC): Nutrition, Physical Activity, and Obesity: Data, Trends and Maps. Available at: https://nccd.cdc.gov/dnpao_dtm/rdPage.aspx?rdReport=DNPAO_DTM.ExploreByTopic&islClass=OWS&islTopic=&go=GO.

Acknowledgements

The authors are grateful to Chaim Fialkoff for helpful comments.

Appendix A1. States-years stratification of observations based on income categories

State	Below $15,000	$15,000–$24,999	$25,000–$34,999	$35,000–$49,999	$50,000–$74,999	Above $75,000	Total
Alabama	10	10	10	10	10	10	60
Alaska	10	10	10	10	10	10	60
Arizona	10	10	10	10	10	10	60
Arkansas	10	10	10	10	10	10	60
California	10	10	10	10	10	10	60
Colorado	10	10	10	10	10	10	60
Connecticut	10	10	10	10	10	10	60
District of Columbia	10	10	10	10	10	10	60
Florida	10	10	10	10	10	10	60
Georgia	10	10	10	10	10	10	60
Hawaii	10	10	10	10	10	10	60
Idaho	7	7	7	7	7	7	42
Illinois	10	10	10	10	10	10	60
Indiana	10	10	10	10	10	10	60
Iowa	10	10	10	10	10	10	60
Kansas	10	10	10	10	10	10	60
Kentucky	10	10	10	10	10	10	60
Louisiana	10	10	10	10	10	10	60
Maine	10	10	10	10	10	10	60
Maryland	10	10	10	10	10	10	60
Massachusetts	10	10	10	10	10	10	60
Michigan	10	10	10	10	10	10	60
Minnesota	10	10	10	10	10	10	60
Mississippi	10	10	10	10	10	10	60
Missouri	10	10	10	10	10	10	60
Montana	10	10	10	10	10	10	60
Nebraska	10	10	10	10	10	10	60
Nevada	10	10	10	10	10	10	60
New Jersey	10	10	10	10	10	10	60
New Mexico	10	10	10	10	10	10	60
New York	10	10	10	10	10	10	60
North Dakota	9	9	9	9	9	9	54
Ohio	10	10	10	10	10	10	60
Oklahoma	10	10	10	10	10	10	60
Oregon	10	10	10	10	10	10	60
Pennsylvania	10	10	10	10	10	10	60
Rhode Island	10	10	10	10	10	10	60
South Dakota	10	10	10	10	10	10	60
Tennessee	10	10	10	10	10	10	60
Texas	10	10	10	10	10	10	60

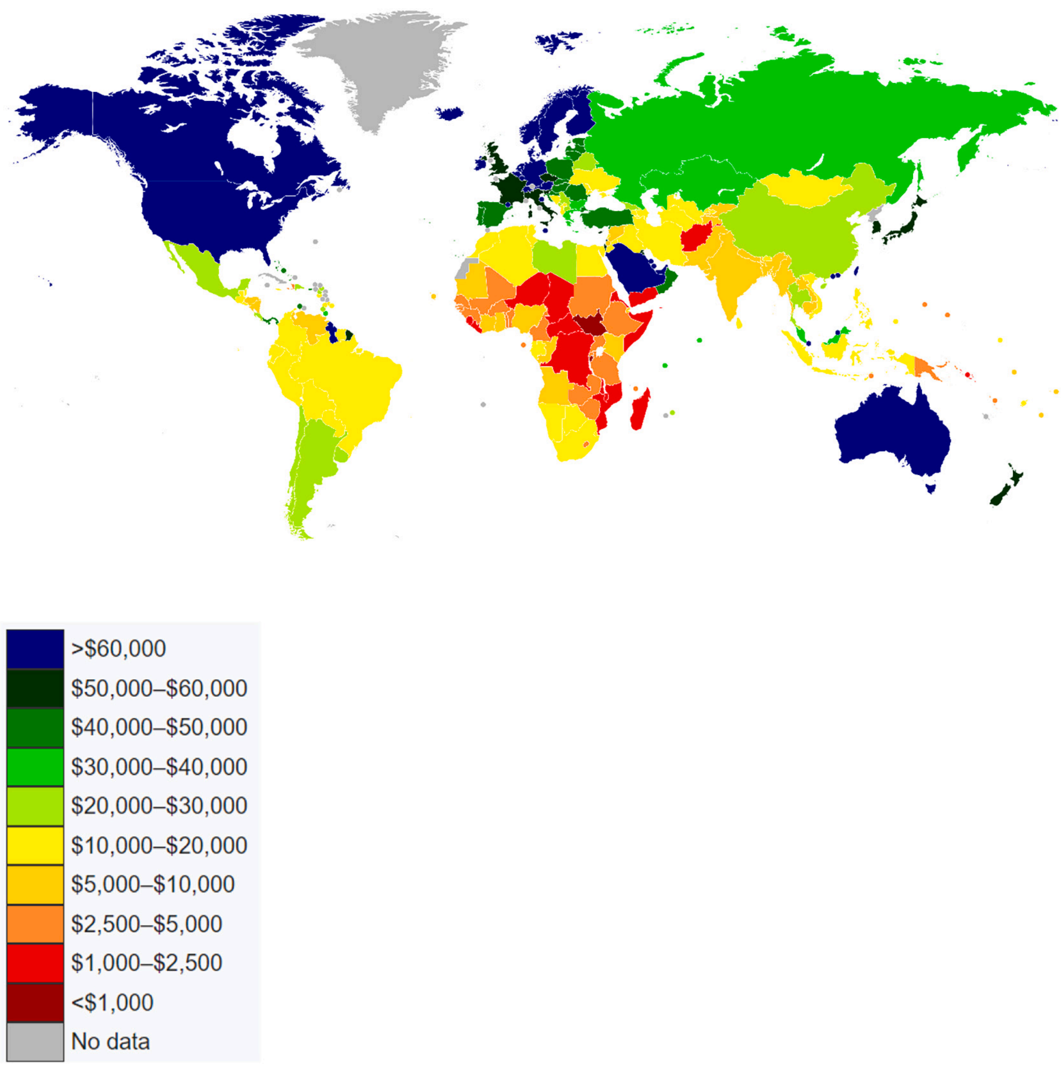
(*continued on next page*)

(*continued*)

State	Below $15,000	$15,000–$24,999	$25,000–$34,999	$35,000–$49,999	$50,000–$74,999	Above $75,000	Total
Utah	8	8	8	8	8	8	48
Vermont	10	10	10	10	10	10	60
Virginia	10	10	10	10	10	10	60
Washington	10	10	10	10	10	10	60
West Virginia	10	10	10	10	10	10	60
Wisconsin	10	10	10	10	10	10	60
Wyoming	10	10	10	10	10	10	60
Total	464	464	464	464	464	464	2784

Source: Centers for Disease Control and Prevention (CDC). Nutrition, Physical Activity, and Obesity: Data, Trends and Maps. Available at: https://nccd.cdc.gov/dnpao_dtm/rdPage.aspx?rdReport=DNPAO_DTM.ExploreByTopic&islClass=OWS&islTopic=&go=GO. Data were extracted by combining the separate files to 2011-2020. The table describes the prevalence of income levels across US states and years. The maximum number of years is 10 (2011–2020).

Appendix A2. World map of countries stratified by per-capita income



Source: The World Bank: GDP Per Capita PPP (Current International $). Available at: https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD?most_recent_value_desc=true&year_high_desc=true.

Appendix A3. List of countries ranked by per-capita GDP

Country/territory	UN region	Estimate	Year	Estimate	Year
Luxembourg	Europe	142,214	2022	115,700	2021
Ireland	Europe	126,905	2022	102,500	2021
Singapore	Asia	127,565	2022	106,000	2021
Liechtenstein	Europe	—	—	139,100	2009
Qatar	Asia	114,648	2022	92,200	2021
Monaco	Europe	—	—	115,700	2015
Macau	Asia	55,344	2022	64,800	2021
Switzerland	Europe	83,598	2022	71,000	2021
United Arab Emirates	Asia	87,729	2022	69,700	2021
Bermuda	Americas	95,837	2022	80,300	2021
Isle of Man	Europe	—	—	84,600	2014
San Marino	Europe	59,451	2020	56,400	2020
Norway	Europe	114,899	2022	65,700	2021
United States	Americas	76,399	2022	63,700	2021
Denmark	Europe	74,005	2022	58,000	2021
Netherlands	Europe	69,577	2022	56,600	2021
Hong Kong	Asia	69,049	2022	60,000	2021
Brunei	Asia	69,275	2022	60,100	2021
Cayman Islands	Americas	74,155	2021	67,500	2021
Taiwan	Asia	—	—	50,500	2017
Falkland Islands	Americas	—	—	70,800	2015
Iceland	Europe	69,081	2022	53,600	2020
Austria	Europe	67,936	2022	54,100	2021
Saudi Arabia	Asia	59,065	2022	44,300	2021
Andorra	Europe	—	—	49,900	2015
Sweden	Europe	64,578	2022	53,600	2021
Germany	Europe	63,150	2022	53,100	2021
Belgium	Europe	65,027	2022	51,700	2021
Australia	Oceania	62,625	2022	49,800	2021
Malta	Europe	55,928	2022	44,700	2021
Gibraltar	Europe	—	—	61,700	2014
Guyana	Americas	40,642	2022	21,900	2021
Bahrain	Asia	61,228	2022	49,400	2021
Finland	Europe	59,027	2022	48,800	2021
Canada	Americas	58,400	2022	47,900	2021
France	Europe	55,493	2022	45,000	2021
European Union	Europe	54,249	2022	44,436	2019
United Kingdom	Europe	54,603	2022	45,000	2021
South Korea	Asia	50,070	2022	44,200	2021
Jersey	Europe	—	—	56,600	2016
Israel	Asia	49,509	2022	42,100	2021
Italy	Europe	51,865	2022	41,900	2021
Cyprus	Asia	49,931	2022	41,700	2021
New Zealand	Oceania	51,967	2022	42,900	2021
Japan	Asia	45,573	2022	40,800	2021
Kuwait	Asia	58,056	2022	43,900	2020
Slovenia	Europe	50,032	2022	40,000	2021
Aruba	Americas	42,698	2021	38,900	2021
Guernsey	Europe	—	—	52,500	2014
Spain	Europe	45,825	2022	37,900	2021
Lithuania	Europe	48,397	2022	39,300	2021
Czech Republic	Europe	49,946	2022	40,700	2020
Poland	Europe	43,269	2022	34,900	2021
Estonia	Europe	46,697	2022	38,700	2021
Saint Pierre and Miquelon	Americas	—	—	46,200	2006
Portugal	Europe	41,452	2022	33,700	2021
Bahamas	Americas	40,379	2022	30,200	2021
Hungary	Europe	41,907	2022	33,600	2021
Croatia	Europe	40,380	2022	31,600	2021
Panama	Americas	39,280	2022	29,000	2021
Slovakia	Europe	37,459	2022	31,900	2021
Turkey	Asia	37,274	2022	31,500	2021
Seychelles	Africa	35,228	2022	28,800	2021
Puerto Rico	Americas	40,498	2022	32,600	2021
Romania	Europe	41,888	2022	30,800	2021
Latvia	Europe	39,956	2022	32,100	2021
Greece	Europe	36,835	2022	29,500	2021
Oman	Asia	41,724	2022	34,300	2021
Greenland	Americas	—	—	41,800	2015
Faroe Islands	Europe	—	—	40,000	2014
U.S. Virgin Islands	Americas	—	—	37,000	2016
Maldives	Asia	24,772	2022	18,800	2021
Malaysia	Asia	33,434	2022	26,300	2021
Sint Maarten (Dutch part)	Americas	41,812	2022	35,300	2018
Guam	Oceania	—	—	35,600	2016
Russia	Europe	36,485	2022	28,000	2021

(continued on next page)

(*continued*)

Country/territory	UN region	Estimate	Year	Estimate	Year
British Virgin Islands	Americas	—	—	34,200	2017
Montserrat	Americas	—	—	34,000	2011
Bulgaria	Europe	33,582	2022	24,400	2020
Kazakhstan	Asia	30,810	2022	26,100	2021
Trinidad and Tobago	Americas	27,778	2022	23,000	2021
New Caledonia	Oceania	—	—	31,100	2015
Chile	Americas	30,209	2022	25,400	2021
Saint Kitts and Nevis	Americas	34,052	2022	26,500	2021
Mauritius	Africa	26,906	2022	21,000	2021
Uruguay	Americas	28,842	2022	22,800	2021
Montenegro	Europe	26,984	2022	20,600	2021
Costa Rica	Americas	24,923	2022	21,200	2021
Argentina	Americas	26,505	2022	21,500	2021
Serbia	Europe	23,911	2022	19,800	2021
Dominican Republic	Americas	22,834	2022	18,600	2021
Antigua and Barbuda	Americas	25,337	2022	19,100	2021
Mexico	Americas	21,512	2022	19,100	2021
Libya	Africa	23,375	2022	22,000	2021
Northern Mariana Islands	Oceania	—	—	24,500	2016
Belarus	Europe	22,591	2022	19,800	2021
China	Asia	21,476	2022	17,600	2021
Curaçao	Americas	22,832	2021	20,800	2021
Thailand	Asia	20,672	2022	17,100	2021
World	World	20,645	2022	17,500	2017
Georgia	Asia	20,113	2022	15,500	2021
North Macedonia	Europe	20,162	2022	16,500	2021
Turks and Caicos Islands	Americas	22,915	2022	18,500	2021
Grenada	Americas	16,987	2022	13,700	2021
Brazil	Americas	17,822	2022	14,100	2020
Iran	Asia	18,075	2022	12,400	2020
Turkmenistan	Asia	15,625	2019	15,000	2019
Armenia	Asia	18,942	2022	14,200	2021
Bosnia and Herzegovina	Europe	20,377	2022	15,700	2021
Albania	Europe	18,552	2022	14,500	2021
Colombia	Americas	20,287	2022	14,600	2021
Botswana	Africa	18,323	2022	14,800	2021
Saint Martin (French part)	Americas	—	—	19,300	2005
Gabon	Africa	16,471	2022	13,800	2021
Saint Lucia	Americas	17,756	2022	13,000	2021
Barbados	Americas	17,837	2022	13,800	2021
Azerbaijan	Asia	17,764	2022	14,400	2021
Equatorial Guinea	Africa	17,396	2022	14,600	2021
Suriname	Americas	17,620	2022	14,800	2021
Saint Vincent and the Grenadines	Americas	17,207	2022	13,700	2021
French Polynesia	Oceania	—	—	17,000	2015
Egypt	Africa	15,091	2022	11,600	2021
Moldova	Europe	15,238	2022	14,000	2021
Cook Islands	Oceania	—	—	16,700	2016
Fiji	Oceania	14,125	2022	10,400	2021
South Africa	Africa	15,905	2022	13,300	2021
Peru	Americas	15,048	2022	12,500	2021
Indonesia	Asia	14,653	2022	11,900	2021
Kosovo	Europe	14,723	2022	11,900	2021
Paraguay	Americas	15,977	2022	13,700	2021
Palau	Oceania	15,145	2021	13,800	2021
Mongolia	Asia	14,230	2022	11,700	2021
Dominica	Americas	13,573	2022	10,900	2021
Ukraine	Europe	12,671	2022	12,900	2021
Bhutan	Asia	11,983	2021	10,900	2021
Vietnam	Asia	13,457	2022	10,600	2021
Sri Lanka	Asia	14,405	2022	13,400	2021
Algeria	Africa	13,210	2022	11,000	2021
Ecuador	Americas	12,822	2022	10,700	2021
Tunisia	Africa	12,490	2022	10,400	2021
Jamaica	Americas	11,822	2022	9600	2021
Jordan	Asia	11,003	2022	9200	2021
Eswatini	Africa	10,782	2022	8900	2021
Lebanon	Asia	14,257	2021	13,000	2021
Iraq	Asia	10,862	2022	9000	2021
Cuba	Americas	—	—	12,300	2016
Anguilla	Americas	—	—	12,200	2008
El Salvador	Americas	11,096	2022	9100	2021
Namibia	Africa	11,206	2022	9100	2021
Philippines	Asia	10,133	2022	8100	2021
Nauru	Oceania	13,118	2022	11,900	2021
American Samoa	Oceania	—	—	11,200	2016

(*continued on next page*)

(*continued*)

Country/territory	UN region	Estimate	Year	Estimate	Year
Belize	Americas	11,451	2022	8800	2021
Guatemala	Americas	10,818	2022	8900	2021
Morocco	Africa	9519	2022	8100	2021
Bolivia	Americas	9684	2022	8100	2021
Uzbekistan	Asia	9533	2022	7700	2021
Cape Verde	Africa	9083	2022	6100	2021
Laos	Asia	9384	2022	7800	2021
India	Asia	8379	2022	6600	2021
Bangladesh	Asia	7395	2022	5900	2021
Venezuela	Americas	17,402	2011	7704	2018
Saint Helena, Ascension and Tristan da Cunha	Africa	—	—	7800	2010
Nicaragua	Americas	6875	2022	5600	2021
Mauritania	Africa	6424	2022	5300	2021
Honduras	Americas	6741	2022	5600	2021
Tonga	Oceania	6749	2021	6100	2021
Angola	Africa	6974	2022	5900	2021
Djibouti	Africa	5893	2022	4900	2021
Ivory Coast	Africa	6538	2022	5300	2021
Ghana	Africa	6498	2022	5400	2021
Pakistan	Asia	6437	2022	5200	2021
Palestine	Asia	6200	2021	5600	2021
Kenya	Africa	5764	2022	4700	2021
Samoa *	Oceania	6041	2022	5500	2021
Kyrgyzstan	Asia	6133	2022	4800	2021
Nigeria	Africa	5860	2022	4900	2021
Marshall Islands	Oceania	7228	2022	6000	2021
Cambodia	Asia	5349	2022	4400	2021
Tokelau	Oceania	—	—	6004	2017
Niue	Oceania	—	—	5800	2003
Tuvalu	Oceania	5421	2022	4900	2021
Congo	Africa	3791	2022	3200	2021
Tajikistan	Asia	4885	2022	3900	2021
Myanmar	Asia	4870	2022	4400	2021
Nepal	Asia	4725	2022	3800	2021
Cameroon	Africa	4408	2022	3700	2021
Senegal	Africa	4209	2022	3500	2021
Benin	Africa	4056	2022	3300	2021
São Tomé and Príncipe	Africa	4738	2022	4100	2020
Zambia	Africa	3894	2022	3200	2021
Micronesia	Oceania	3855	2022	3300	2021
East Timor	Asia	4828	2022	5000	2021
Ethiopia	Africa	2812	2022	2300	2021
Sudan	Africa	4216	2022	3700	2021
Tanzania	Africa	3097	2022	2600	2021
Comoros	Africa	3832	2022	3200	2021
Papua New Guinea	Oceania	4447	2022	3700	2022
Wallis and Futuna	Oceania	—	—	3800	2004
Guinea	Africa	3187	2022	2600	2021
Lesotho	Africa	2695	2022	2300	2021
Uganda	Africa	2694	2022	2200	2021
Haiti	Americas	3305	2022	2900	2021
Rwanda	Africa	2792	2022	2200	2021
Guinea-Bissau	Africa	2190	2022	1800	2021
Vanuatu	Oceania	3289	2022	2800	2021
Syria	Asia	—	—	2900	2015
Gambia	Africa	2510	2022	2100	2021
Togo	Africa	2608	2022	2100	2021
Burkina Faso	Africa	2546	2022	2200	2021
Mali	Africa	2517	2022	2100	2021
Zimbabwe	Africa	2531	2022	2100	2021
Solomon Islands	Oceania	2654	2022	2400	2021
Kiribati	Oceania	2365	2022	1900	2021
Eritrea	Africa	1629	2011	1600	2017
Sierra Leone	Africa	1931	2022	1600	2021
Yemen	Asia	3437	2013	2500	2017
Somalia	Africa	1364	2022	1100	2021
Afghanistan	Asia	1674	2021	1500	2021
Madagascar	Africa	1774	2022	1500	2021
Chad	Africa	1668	2022	1400	2021
Liberia	Africa	1725	2022	1400	2021
North Korea	Asia	—	—	1700	2015
Malawi	Africa	1732	2022	1500	2021
Niger	Africa	1505	2022	1200	2021
Mozambique	Africa	1468	2022	1200	2021

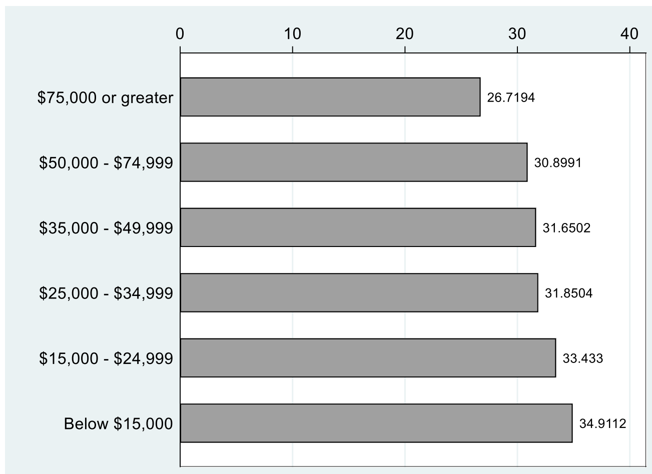
(*continued on next page*)

(*continued*)

Country/territory	UN region	Estimate	Year	Estimate	Year
DR Congo	Africa	1337	2022	1100	2021
Central African Republic	Africa	967	2022	800	2021
Burundi	Africa	836	2022	700	2021
South Sudan	Africa	1182	2015	1600	2017

Source: The World Bank: GDP Per Capita PPP (Current International $). Available at: https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD?most_recent_value_desc=true&year_high_desc=true.

Appendix A4. Average percent of obese population (*BMI*≥30) stratified by income levels



Appendix A5. Obesity prevalence based on each income category

Variables	(1)	(2)
	Sample mean (obesity prevalence)	Obesity prevalence
$75,000 or greater	26.7194	−8.1918*** (<0.01)
$50,000–$74,999	30.8991	−4.0121*** (<0.01)
35,000–$49,999	31.6502	−3.2610*** (<0.01)
$25,000–$34,999	31.8504	−3.0608*** (<0.01)
$15,000–$24,999	33.433	−1.4782*** (<0.01)
Below $15,000	34.9112	34.9112*** (<0.01)
Observations	2784	2,784
R-squared		0.2314

Notes: The income categories are dummy variables that equal 1 for that category and 0 for other categories. Column (1) gives the sample meaning of obesity prevalence for each income category. Column (2) gives the difference between the base category (below $15,000) and each of the other categories. Numbers in parentheses are *p*-values.

*** $p < 0.01$.

References

Arbel, Y., Fialkoff, C., & Kerner, A. (2022). Is there an endogeneity problem between health and apartment value? Gender differences and the impact of obesity on property self-evaluation. *Journal of Housing and the Built Environment, 37*, 807–822. https://doi.org/10.1007/s10901-021-09879-0

Centers for Disease Control and Prevention (CDC). Nutrition, physical activity, and obesity: Data, trends and maps. Available at: https://nccd.cdc.gov/dnpao_dtm/rdPage.aspx?rdReport=DNPAO_DTM.ExploreByTopic&islClass=OWS&islTopic=&go=GO.

Chiang, A., & Wainwright, K. (2005). Fundamental methods of mathematical economics. In *McGraw Hills international edition* (4th ed.).

Cooper, K., & Stewart, K. (2021). Does household income affect children's outcomes? A systematic review of the evidence. *Child Indicators Research: The Official Journal of the International Society for Child Indicators, 14*(3), 981–1005. https://doi.org/10.1007/s12187-020-09782-0

Dwijendra, N., Akhmadeev, R., Tumanov, D., Kosov, M., Shoar, S., & Banaitis, A. (2021). Modeling social impacts of high-rise residential buildings during the post-occupancy phase using DEMATEL method: A case study. *Buildings, 11*(504), 504. https://doi.org/10.3390/buildings11110504

Gifford, R. (2007). The consequences of living in high-rise buildings. *Architectural Science Review, 50*(1), 2–17. https://doi.org/10.3763/asre.2007.5002

Glaeser, E. (2011). *The triumph of the city*. Penguin Books (Printed in the United States of America).

Manstead, A. S. R. (2018). The psychology of social class: How socioeconomic status impacts thought, feelings, and behaviour. *British Journal of Social Psychology, 57*(2), 267–291. https://doi.org/10.1111/bjso.12251

Morrish, N., & Medina-Lara, A. (2021). Does unemployment lead to greater levels of loneliness? A systematic review. *Social Science & Medicine, 287*. https://doi.org/10.1016/j.socscimed.2021.114339 (N.PAG).

Panczak, R., Galobardes, B., Spoerri, A., Zwahlen, M., & Egger, M. (2013). High life in the sky? Mortality by floor of residence in Switzerland. *European Journal of Epidemiology, 28*(6), 453–462. https://doi.org/10.1007/s10654-013-9809-8

Ramanathan, R. (2002). *Introductory econometrics with applications* (5th ed.). South Western Thomson Learning.

Tapia-Muñoz, T., Staudinger, U. M., Allel, K., Steptoe, A., Miranda-Castillo, C., Medina, J. T., & Calvo, E. (2022). Income inequality and its relationship with loneliness prevalence: A cross-sectional study among older adults in the US and 16 European countries. *PLoS One, 17*(12), Article e0274518. https://doi.org/10.1371/journal.pone.0274518

Woolf, S. H., Aron, L., Dubay, L., Simon, M. S., Zimmerman, E., & Luk, K. X. (2015). How are income and wealth linked to health and longevity? *The Urban Institute*, 1–21.