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# Perspective: Some Causal and Priority Language about Food Energy Supply as the Sufficient Cause of the Obesity Pandemic is Premature or Incorrect

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**14. ABSTRACT**

Several obesity experts have claimed the growth in food supply after 1965 was the primary cause of the global obesity pandemic based on ecologic data. Using public access global data we explored per capita food supply and two metabolic diseases (i.e., obesity and raised fasting glucose). We also compared overweight military service members who were semi-randomly assigned to countries with variable food supply and observed obesity outcomes for 7 years. Among countries with 2008 food supply above the United States' in 1965 (2,926 kcal per capita per day), higher national supply was paradoxically associated with lower prevalence of raised fasting glucose (e.g., $r = -0.42$, $p \leq 0.001$). Obesity incidence in military members showed a similar association. The causal effect and relative importance of national food energy supply are difficult to determine from observational data. Our perspective is that the combination of causal and priority language could be misinterpreted as though there is one scientifically proven cause that fully explains the obesity epidemic.

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# ACKNOWLEDGMENTS

Mr. Gi-Taik Oh provided valuable technical assistance in compiling these data. No funding was obtained for this study. Some of the original data used for this analysis is archived with the Armed Forces Health Surveillance Center and data availability is subject to their policies and procedures.

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## 1.0 SUMMARY

Several obesity experts have claimed the growth in food supply after 1965 was the primary cause of the global obesity pandemic based on ecologic data. Using public access global data we explored per capita food supply and two metabolic diseases (i.e., obesity and raised fasting glucose). We also compared overweight military service members who were semi-randomly assigned to countries with variable food supply and observed obesity outcomes for 7 years. Among countries with 2008 food supply above the United States' in 1965 (2,926 kcal per capita per day), higher national supply was paradoxically associated with lower prevalence of raised fasting glucose (e.g., $r = -0.42$, $p \leq 0.001$). Obesity incidence in military members showed a similar association. The causal effect and relative importance of national food energy supply are difficult to determine from observational data. Our perspective is that the combination of causal and priority language could be misinterpreted as though there is one scientifically proven cause that fully explains the obesity epidemic.

## 2.0 INTRODUCTION

Over the past several decades, obesity and diabetes have become more prevalent throughout the world (i.e., pandemic), and this raises well-documented economic, public health, social, and national security concerns. Obesity has a multifactorial etiology [1], but several obesity experts have suggested food energy supply alone as the principal historic cause of the obesity pandemic. Public claims have ranged in nuance and force, but they often include causal and priority language that together could be misinterpreted. Words with a connotation about a cause and effect relationship include increase, effect, driver, and cause [2], while claims suggesting priority include terms like predominant, focus, major, dramatic, sufficient, etc. Editorials and press interviews with experts have featured claims such as "The epidemic was caused by the overproduction of food" [3] and "Resoundingly, the consensus is building that to reverse the obesity epidemic, the focus must be on food and the 'push effect' of the food supply" [4]. Other editorials have claimed that we should prioritize "supply side drivers" of obesity [5]. One research paper with a title describing food supply as "a Major Driver" of global obesity said, "Increases in food energy supply are sufficient to explain increases in average population weight" [6,7], while another described the food supply increase as "dramatic" [8]. Although causal language is commonly misused in obesity literature [3,9], the combination with priority language could be misinterpreted as though all other factors made no contribution to the obesity pandemic (which is likely untrue [1]). For instance, a "sufficient cause" is deterministic by itself without any additional cofactors.

Despite strong language, the hypothesis remains unproven and difficult to test depending on how it is constructed. In general, the "push effect" claims an "obesogenic" food supply causes "passive overconsumption" [5] (i.e., the mere existence of food pushes itself into passive residents). Therefore, it is often framed or evaluated based on calories in the national food supply [5-8] or even reduced to "food production" and said to be simple math [3,10]. An "overproduction" of food is thought to increase supply and lower food cost [3]. The hypothesis also proposes that lower cost causes overconsumption, raising body weight and causing the obesity epidemic. Although it is an unproven hypothesis, ecologic observations of food prices [11] are often misinterpreted with headlines like "Report: Cheap food makes us fat" [12]. These and other similar ecologic observations in the United States [7,8] are not a basis for causal claims and may not be generalizable worldwide.

Other analyses have evaluated global data on changes in food supply and changes in body weight over time [6,13]. One limitation with this strategy is that the obesity pandemic occurred during a rapid transition where many factors changed in addition to food supply (e.g., medication use, development, motorized transport, globalization, sanitation, etc.) [14,15], so all long-term trends (i.e., secular trends) confound time trend ecological studies. Thus, we investigated cross-sectional global ecological data and used absolute levels of food availability, controlling for secular trends by using the same snapshot in time across all countries.

Aside from specific limitations, general concerns about causal claims from ecological data are the inability to assess directionality and ecological fallacy. How can we measure whether citizens are passive? Could higher weight alter demand for food and thus increase supply? In at least one ecologic analysis, when food was more likely to be purchased outside rather than inside the county, "insufficient" supply was associated with higher body mass index [16], suggesting the possibility of reverse causation. Additionally, ecological fallacy refers to the possibility that ecological associations may not be valid because population-wide exposure and outcome covariance may not reflect covariance between outcome and exposure among individuals. Interestingly, observational studies at the individual level [17-22] do not find decreased obesity associated with lower reported individual food supply (i.e., food insecurity).

Although an improvement from ecological data, these individual-level study designs were still observational and thus limited by the potential for confounding and reverse causation. Subjects should be randomly assigned to varying amounts of food supply and monitored over many years. To investigate this question more rigorously, we present a 7-year follow-up study of observational data from the U.S. military, which prior empiric analysis has shown approximates random assignment [23]. Individuals assigned to multiple exposures simultaneously approximated a recently described study design called "packet randomized experiment" (PRE) [24]. By using both the PRE data and the previously described global ecological data, we seek to evaluate whether nationwide food supply is associated with obesity. Additionally, because of limitations in international comparisons of obesity based on body mass index (BMI) [25], we also evaluated prevalence of raised fasting glucose (RFG) because, like obesity, nationwide prevalence of RFG is available from public access data sources.

## 3.0 METHODS

Analyses of preexisting de-identified datasets for the ecological and quasi-experimental study have been reported [23,26,27]. The Air Force Research Laboratory Institutional Review Board at Wright-Patterson Air Force Base, Ohio, determined that analysis of the de-identified data initially derived from the longitudinal database of military medical records (Defense Medical Surveillance System) was non-human subjects research and amended the prior determination [23] to include the present use of these data.

### 3.1 Ecological Study

Briefly, global data on food energy supply were obtained from the Food and Agriculture Organization's publicly accessible data for 2008 [28]. Because international comparisons of BMI are controversial [25], we included both 2008 obesity (BMI $\geq$ 30 kg/m$^2$) and 2008 RFG (single reading ≥ 126 mg/dL or on medication) as outcomes based on publicly accessible modeled or measured data obtained from the World Health Organization (WHO). These figures are age-adjusted by WHO to account for differing age demographics. The datasets from 2008 were the most recent available at the time of analysis. Next, we stratified the datasets between countries with 2008 food availability above and below the level of food energy availability in the United States in 1965. Aside from international data availability, the year 1965 is an appropriate starting point because food availability in the United States reached its century long nadir by 1965 [3], and the prevalence of obesity [29] and diabetes [30] in the United States began rising rapidly after 1965. Statistical analysis was conducted by calculating correlation coefficients with SAS v.9.3 (SAS Institute, Inc., Cary, NC) and linear regression and Lowess smoothing with Stata v.12.0 (StataCorp, College Station, TX).

### 3.2 Packet Randomized Experiment

Briefly, military enlistees with a BMI between ≥ 25 kg/m$^2$ and < 30 kg/m$^2$ at time of enlistment and with 2 years of service in the Army or Air Force were followed from January 2006 through December 2012 for up to 7 years (or until the time of separation/reassignment or obesity diagnosis if these occurred before December 2012). Time reset to zero when the service member was assigned to another location (e.g., permanent transfer from Germany to Japan). Only four countries (Germany, Japan, South Korea, and the United Kingdom) were included because the de-identification process by the Armed Forces Health Surveillance Center used three-digit ZIP (postal) codes to identify location. These are the only countries identified by specific three-digit ZIP codes (aside from the Philippines, which was excluded because it only provided 11 observations) [31]. The outcome of interest was based on obesity-related International Classification of Diseases, Ninth Revision codes (278.01-2; V85.3+ series). Clinical obesity diagnoses are specific for obese BMI [32], and within the military, they predict atherosclerosis and military separation [33,34]. These data were combined with 2009 Food and Agriculture Organization food availability and represent the mid-point of the 7-year study. Cox regression analysis accounting for repeated observations was conducted using Stata v.12.0 (StataCorp, College Station, TX) as previously described [23].

## 4.0 RESULTS

### 4.1 Ecological Study

We found the association between food energy availability and both types of metabolic disease concave (i.e., it differed above and below per capita supply of 2,926 kcal) as shown in Figure 1.

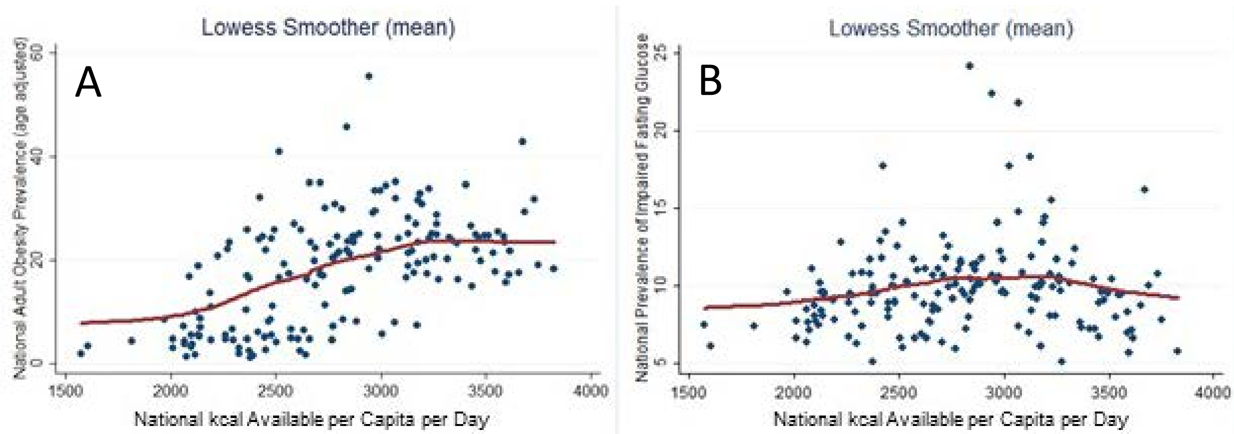


**Figure 1. Relationship between 2008 national food availability (A) and 2008 metabolic disease (B).**

There was a direct correlation between food availability and metabolic diseases among countries with food availability below U.S. levels in 1965. However, among 67 countries with 2008 national food availability above U.S. levels in 1965 (2,926 kcal per capita per day), there was an inverse relationship with impaired fasting glucose ($r = -0.42$, $p \leq 0.001$) and a non-significant inverse association with obesity ($r = -0.13$, $p = 0.31$) in a negative correlation direction. When considering only those countries (more historically similar to the United States) that also had more than 2,926 kcal per capita per day of food available in 1965, these relationships are more prominent (Figure 2).

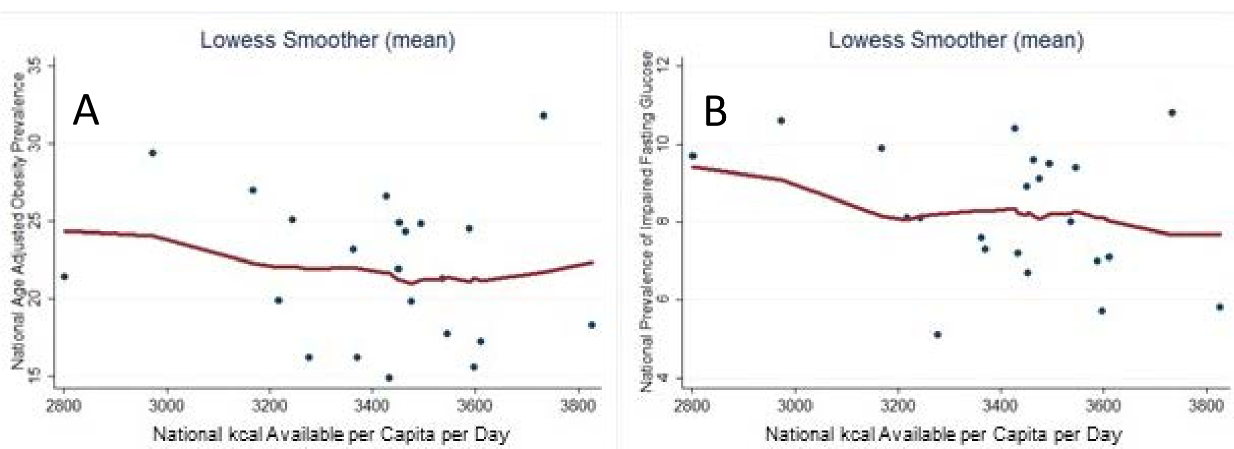


**Figure 2. Relationships between 2008 national food availability (A) and 2008 metabolic diseases (B) for countries that (similar to the United States) also had 2926 kcal available per capita per day in 1965.**

### 4.2 Packet Randomized Experiment

There were 58,827 person-years of observation from 52,669 "segments" (n = 19,000 Air Force segments and n = 33,669 Army segments) or periods of time observed at an assigned duty location after excluding censored time, thus averaging 1.1 years per segment. When considering food energy availability as a continuous variable, the associations with new onset obesity diagnoses within the Air Force (hazard ratio [HR] = 0.92 per 500 kcal; 95% confidence interval [CI] 0.84 – 1.00; $p < 0.04$) and Army (HR = 0.90 per 500 kcal, 95% CI 0.75 – 1.08; $p > 0.05$) were similar to one another. The similarity between those in the Air Force (HR = 0.92 per 500 kcal; 95% CI 0.84 – 1.00; $p = 0.04$) and Army (HR = 0.93 per 500 kcal; 95% CI 0.77 – 1.12; $p > 0.05$) remained after adjusting for baseline BMI at time of enlistment, age, sex, time in service, race/ethnicity, and occupation type. Thus, combining both services and adjusting for branch of service was also similar (HR = 0.91 per 500 kcal; 95% CI 0.84 – 0.98; $p = 0.01$).

When considering individual countries as a categorical variable, each pair wise country comparison among those in the Army showed the hazard of obesity was not statistically different ($p > 0.05$). However, among those in the Air Force, living in the country with the lowest food availability (Japan) was associated with a higher hazard of obesity compared to those living in South Korea (HR = 0.52 per 500 kcal; 95% CI 0.43 – 0.63; $p < 0.001$) or Germany (HR = 0.85 per 500 kcal; 95% CI 0.74 – 0.97; $p = 0.01$). There was also a trend toward a higher hazard in Japan than among those living in the United Kingdom (HR = 0.93; 95% CI 0.80 – 1.08; $p > 0.05$). A comparison of Air Force members living in each of the four countries (Figure 3) can be visualized as the cumulative hazard function of developing an obesity diagnosis. Although enlistment BMI was similar regardless of where an Air Force enlistee was assigned, there were other differences in demographic features (i.e., age, sex, time in service, race/ethnicity, and occupation) among those assigned to different countries (Table 1). Despite these demographic differences, aggregate confounding was low, as the pattern of association was similar after adjusting for baseline BMI at time of enlistment, age, sex, time in service, race/ethnicity, and occupation type (Table 2).

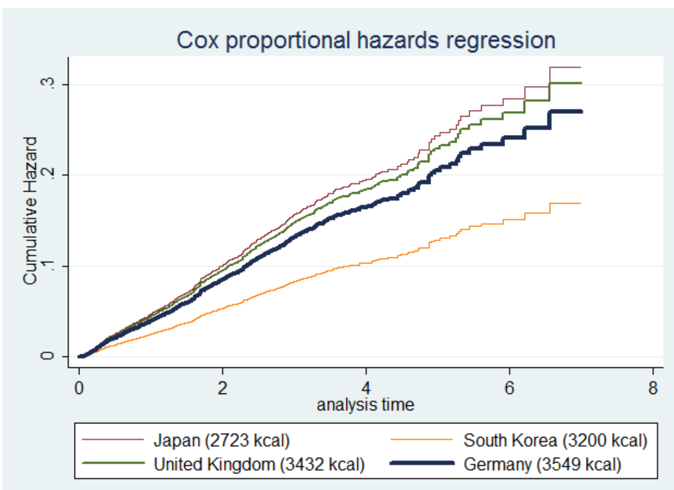


**Figure 3. Cumulative hazard function for Air Force members by country (food availability in kcal/capita/day).**

**Table 1. Demographic Features by Country Assignment Among Air Force Members**

| Baseline Covariates | South Korea | Japan | Germany | United Kingdom | p-value[a] |
|---|---|---|---|---|---|
| Sample, total person-years (1,000s) | 5.9 | 8.0 | 9.0 | 5.4 | ------ |
| Baseline BMI, mean (kg/m$^2$) | 26.6 (26.6) | 26.6 (26.6) | 26.6 (26.5) | 26.6 (26.5) | p=0.33 |
| Age, mean (yr) | 28.1 (28.0) | 27.0 (27.2) | 27.4 (27.5) | 26.9 (27.2) | p<0.001 |
| Time in service, mean (yr) | 8.1 (8.0) | 7.5 (7.5) | 7.8 (7.6) | 7.5 (7.5) | p<0.001 |
| Sex, male (%) | 93 (94) | 93 (93) | 92 (92) | 91 (92) | p=0.002 |
| Occupation | | | | | |
| Armor/transport (column %) | 1 (1) | 2 (2) | 1 (1) | 1 (1) | |
| Communications/intelligence (%) | 24 (24) | 22 (22) | 28 (28) | 23 (23) | |
| Health care (%) | 4 (4) | 5 (6) | 6 (5) | 5 (5) | |
| Infantry/artillery/combat (%) | 0 (0) | 0 (0) | 0 (1) | 1 (0) | p<0.001 |
| Other (%) | 16 (16) | 16 (15) | 21 (20) | 17 (17) | |
| Repair/engineer (%) | 54 (54) | 53 (53) | 43 (45) | 51 (51) | |
| Pilot/air crew (%) | 0 (0) | 2 (2) | 1 (1) | 2 (2) | |
| Race/Ethnicity | | | | | |
| Asian (column %) | 6 (6) | 8 (9) | 4 (4) | 4 (5) | |
| African American (%) | 20 (20) | 19 (19) | 15 (14) | 15 (14) | |
| Hispanic (%) | 10 (10) | 10 (10) | 11 (11) | 9 (10) | |
| American Indian (%) | 1 (1) | 1 (1) | 1 (1) | 1 (1) | p<0.001 |
| Other race (%) | 3 (3) | 3 (3) | 2 (2) | 2 (2) | |
| White (%) | 58 (58) | 56 (54) | 64 (64) | 66 (66) | |
| Unknown (%) | 3 (4) | 3 (3) | 4 (4) | 3 (3) | |

Note: The p-values are based on analysis of variance test for continuous comparisons and chi-square test of homogeneity to compare proportions. Frequency weighting by person-time is provided in parenthesis.

[a]The observations were not necessarily independent of one another. Although assumptions implied by Table 1 were not necessarily met, because Table 1 describes the differences between groups, these assumptions represent a conservative estimate.

**Table 2. Demographic Features by Country Assignment for Air Force Members**

| Country | Food Energy Available (kcal) | Crude HR (95% CI) | Adjusted HR (95% CI)[a] |
|---|---|---|---|
| Japan | 2723 | Referent | Referent |
| South Korea | 3200 | 0.52 (0.43–0.63) | 0.53 (0.44–0.64) |
| United Kingdom | 3432 | 0.93 (0.80–1.08) | 0.94 (0.81–1.10) |
| Germany | 3549 | 0.85 (0.74–0.97) | 0.85 (0.74–0.97) |

[a]HR adjusted for baseline BMI at time of enlistment, age, sex, time in service, race/ethnicity, and occupation type.

## 5.0 DISCUSSION

Global food availability has a concave association with obesity and raised fasting glucose, as food energy supply above U.S. levels in 1965 has a significant inverse association with RFG prevalence and a similar direction but non-significant association with obesity prevalence (Figure 1). A concave association has been previously shown for obesity and surrogates of food supply (e.g., education, income, and urbanization) [35-39]. Furthermore, no country with a food supply as abundant as the United States in 1965 has avoided the obesity pandemic. That is, a hyper-abundant food supply far beyond living requirements (nearly 3,000 kcal/person/day) was not sufficient to cause pandemic disease in 1965 even though it is universally associated with pandemic disease by 2008, arguing against supply-related determinism. Similarly, the PRE data showed a similar pattern as the ecological data, with higher food availability associated with less obesity among military members. The PRE data also demonstrated empiric evidence (similarity of adjusted HR and unadjusted HR) that subjects were not different from one another, which is consistent with semi-random exposure assignment [23]. We evaluated the total energy in the food supply, which has been used in numerous papers advocating the "push effect" [3-8]. Others consider food energy supply a part of the equation, but that the "push effect" is really about lowered food price causing obesity where price is considered more broadly as financial cost, time, and labor "costs" [10]. However, experimental data, where convenience was improved or food cost decreased, do not always support this hypothesis. For instance, studies where individuals are provided convenient (and no-cost) lower energy food to replace a meal are so consistent in producing additional weight loss, it has been described as an obesity fact (although obesity and weight change are not interchangeable) [40]. Similar findings were also shown in a study of working adults (n = 223) randomized to four groups [41]. Consistent with other studies, conveniently providing free on-site meals (either 400 kcal or 800 kcal) on work days for 6 months prevented weight gain (both these groups lost 0.1 kg) [41]. However, the benefit of the free meals was erased in a third group when the meals were 1,600-kcal portions, as this group gained the same amount of body weight (1.1 kg) as a control group who had to obtain food at their own cost. By contrast, intermittently eliminating food availability causes fat deposition and signs of metabolic syndrome in mice as compared with mice eating more calories with a continuously available diet [42]. Also, a small (n = 32) randomized crossover trial in women showed delaying lunch until 4:30 p.m. worsened glucose tolerance [43].

Similar with food convenience, the spatial distribution of food outlets has also been proposed as a factor in weight gain (microenvironment vs. macroenvironment). For instance, in the United Kingdom, aggregated exposure to takeout food along a person's commuting route, while at work, and while at home is associated with weight gain [44]. Similarly, among school children, weight gain is associated with fast-food restaurant location at 0.16 km (0.1 mi) but not associated at 0.40 km (0.25 mi) [45]. If localized associations remain confined, it could suggest local distribution factors are more important than systemic production. However, we could not assess localized factors because we did not have housing addresses. Overall, about 55,000 overseas military members live outside the base in the host nation community [46], but (perhaps importantly for future investigation) this is probably less common in Japan [47]. The environment within the installation was measured in 2011 with the Military Nutrition Environment Assessment Tool (m-NEAT), but these data show the only Japanese base is better in all six categories than the only South Korean base with available data (Table 3).

**Table 3. All Available m-NEAT Scores for Air Force Installations within Japan and South Korea in 2009**

| Category[a] | Air Force Average | Japan (Yokota) | South Korea (Kunsan) |
|---|---|---|---|
| Military Dining | 71 | n/a | 62 |
| IMT DFAC | 78 | 84 | n/a |
| Convenience Stores | 82 | 94 | 58 |
| Sit Down Restaurants | 61 | 84 | 58 |
| Fast Food Restaurants | 55 | 91 | 45 |
| NRVM Not Barracks | 43 | 62 | 29 |
| Refrigerated VM | 40 | 100 | 25 |
| NRVM in Barracks | 47 | 71 | n/a |
| Worksite Setting | 79 | 100 | 75 |
| Fitness | n/a | n/a | 44 |

Note: Overall scoring: 75-100 = Fully Supportive; 50-74 = Mostly Supportive, <50 = Not/Partially Supportive.
[a]IMT DFAC = Initial Military Training Dining Facility; NR = non-refrigerated; VM = vending machine.

Interestingly, as another description of conclusiveness, some advocating the "push effect" have also argued against the use of particular study designs, specifically dismissing the two methods of analysis we present. For instance, one author argued against using cross-sectional studies in obesity investigations because it obscures the long-term [ecological] pattern between the time cost of food and obesity [10]. It seems premature to determine which methods are appropriate based on how clearly they demonstrate a given hypothesis. We believe cross-sectional studies are still worthwhile, as numerous obesity etiologies unrelated to the food environment (e.g., indoor temperature, smoking cessation, sleep, etc.) have temporal associations with the obesity pandemic [15,16]. By using cross-sectional data, we can control for secular trends unrelated to the exposure of interest by evaluating all countries at the same time.

Other authors have said it is "not practical" to randomize individuals to differing food environments, but practicality is not defined [6]. As practicality relates to complexity and risk, an important question is how does the difficulty of such a study compare with the challenges associated with efforts to control the global food supply? While difficult to answer, we know of at least three opportunities for semi-randomly assigning humans to different food environments previously demonstrating low cost and risk. In the present analysis, military members are assigned to different environments. Empirically, the assignment appeared "as if" random [23]. Additionally, international adoptees have been randomly assigned to live with adoptive parents in different locations [24]. Finally, foreign exchange students could be randomly assigned to different environments [48]. Further, one might argue other exposures (e.g., microenvironment, investment from parents, campus experience, etc.) would be more important than the national food energy supply. Packet level confounding would remain possible, but if present, it would argue against the priority claims made by advocates of the push hypothesis [4-6]. Additionally, bounded inferences about the aggregated effect of all these factors can be evaluated using covariance algebra and instrumental variables [24]. It would be helpful to investigate more populations because a positive or negative effect of an abundant food environment could be population dependent.

Other probative methods of inquiry are also available. Cluster randomization could be used to randomize units of area (e.g., communities, nations) to different food environments or different interventions attempting to alter food environment. We know of at least three natural experiments of altered national food supply that support the concave association in the cross-sectional data. Although not a basis for causal inferences, in two low income countries (Cuba and Nauru), economic hardship was associated with further lowering of food supply and subsequent improvement in obesity, but there are other explanations for this association [5,49,50]. By contrast, in the United States, corporations pledged to reduce food supply from 2007-2012 and food supply was reduced by 78 kcal per capita/day [51], but this coincides with worsening population level trends in average waist circumference, severe obesity, and inequalities [52,53].

## 6.0 CONCLUSIONS

Food supply, obesity prevalence, and RFG prevalence have recently gone up throughout the world. However, it remains unproven whether food supply is the sufficient explanation for obesity trends in the developed world. In fact, the associations between food supply and metabolic diseases (i.e., obesity and RFG) in both the ecological and PRE studies do not provide additional support for prior claims. Rather, the association appears concave, context/population dependent, subject to other challenges with measurement, and/or less important than confounders do. Although our data have limitations that couldn't fully test the push hypothesis, we have shown the PRE method is possible and offered further options for better probing complex causal contributions.

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## LIST OF ABBREVIATIONS AND ACRONYMS

| | |
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| **BMI** | body mass index |
| **CI** | confidence interval |
| **HR** | hazard ratio |
| **m-NEAT** | military nutrition environment assessment tool |
| **PRE** | package randomized experiment |
| **RFG** | raised fasting glucose |
| **WHO** | World Health Organization |