DOWNLOAD PDF EPIDEMIOLOGICAL PRACTICES IN RESEARCH ON SMALL EFFECTS

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Epidemiology faces its limits: the search for subtle links between diet, lifestyle, or environmental factors and disease is an unending source of fear - but often yields little certainty. Studies on weak associations - or small effects - often produce contradictory results which confuse the public.

Advanced Search Abstract Background Large studies may identify postulated risk factors and interventions with very small effect sizes. We aimed to assess empirically a large number of statistically significant relative risks RRs of tiny magnitude and their interpretation by investigators. Methods RRs in the range between 0. We also calculated the probability that each effect lies outside specific intervals around the null RR interval 0. Results We evaluated 51 eligible tiny effects median sample size for risk factors and 36 for interventions. No concerns were expressed for 28 effects. Conclusions Statistically significant tiny effects for risk factors and interventions of clinical or public health importance become more common in the literature. Cautious interpretation is warranted, since most of these effects could be eliminated with even minimal biases and their importance is uncertain. Small effect size , tiny effect magnitude , observational study , meta-analysis , risk factor , intervention Introduction Biomedical studies sometimes come across small effects of risk factors and interventions. Effects of risk factors and interventions are important to interpret appropriately, regardless of their magnitude. Some very small effects may still have clinical and public health relevance, e. However, when effect sizes are tiny, using the nominal statistical significance for making inferences is problematic. In this setting, frequentist and Bayesian approaches may reach opposite conclusions. Here, we examined empirically the studies that documented and highlighted relative risks RRs in the range of 0. We aimed to describe what these effects are; to calculate the probability that these results are compatible with effects of various magnitude; and whether the authors raise any appropriate caveats when interpreting such tiny effects. Methods Definitions We considered effects sizes in any RR scale that had values between 0. Any RR scale metric was eligible, including odds ratio, risk ratio, hazard ratio and relative incidence ratio. For consistency, we only examined effects pertaining to binary outcomes. We considered as eligible all risk factors and interventions that were binary and those that were categorical with more than two categories, or took discrete values, provided that an RR was given for some contrast of specific categories, or per one or more units for discrete variables e. The same applied to risk factors that were continuous but treated as categorical with two or more categories by their investigators. For risk factors that were continuous and treated as such in the analysis, we considered them eligible only if the RR was expressed per an amount of exposure other than just one point of the raw measurement values. This guaranteed that the investigators had selected to present the effect for a contrast that they considered a meaningful amount of exposure and did not just automatically express the risk per one point of the continuous variable. We accepted the discretion of the authors on what they considered a meaningful amount of contrast. RRs per one point may actually correspond to substantial effects, when expressed in more meaningful contrasts. Search strategies for eligible studies Detecting all reported tiny effects for all biomedical research is impossible and unnecessary for an empirical evaluation. Moreover, many tiny effects are considered unimportant and either get buried in fine print or remain unreported. Conversely, here we aimed to identify a convenience sample of eligible tiny effects that were considered important enough by their authors to mention them in the abstracts of the respective papers. We collected a sample of such tiny effects from three searches targeting articles from large cohort studies, articles published in major general medical journals and meta-analyses of interventions. Large cohorts are theoretically more likely to encounter nominally statistically significant tiny effects, given their very large sample sizes, which give them maximal power to detect tiny effects. General medical journals have high impact on clinical and public health practice. Finally, meta-analyses can also accumulate large sample sizes and have high power to show nominally significant tiny effects, and are also considered very influential for clinical practice and public health. Searches of the literature were performed in PubMed last update August

We accepted eligible estimates reported by cohort studies, regardless of whether they had been observed in 1 of these specific 12 cohorts, or some other cohort that happened to also mention one of these keywords in the abstract. For the third search, we screened all systematic reviews of randomized trials published in the Cochrane Database of Systematic Reviews. When the same topic had been covered in serially updated reviews, we considered only the most recent update. For all three searches, we applied as search terms all the numbers in the range between 0. All the retrieved items were initially scrutinized for eligibility in abstract level. In the abstract, we examined whether these selected numbers referred to an eligible RR point estimate and also whether the full text of the article was in English language. If so, the article was deemed potentially eligible, and the full text was retrieved for in-depth evaluation. When more than one eligible RR estimate was found in an abstract, these were considered as separate effects. Data extraction For each eligible study and effect estimate, we extracted the first author, journal, year of publication, total sample size, effect metric, risk factor or intervention, study population under evaluation and corresponding outcome. We categorized risk factors as binary, categorical with more than two categories, discrete, continuous-treated-as categorical and continuous and recorded the measure of interest and the exposure contrast chosen by the investigators to express the reported RR. Appraisal by investigators We recorded verbatim for each of the eligible effects what the authors had inferred from these results. The Abstract, Results and Discussion sections were scrutinized for any comment on the provided tiny effect s in each of the eligible studies. For observational studies, we recorded whether the authors expressed any caveat; and, if so, whether their concerns pertained to the small effect size, residual confounding or other reasons. For interventions meta-analyses or randomized controlled trials , similarly, we recorded whether the effect was considered clinically relevant without any caveat; or caveats were mentioned about the small effect size, bias or other reasons. Whenever raw data were available, we recalculated the RR so as to obtain higher precision for the effect and standard error square root of the variance. The point estimate was approximated with greater precision three decimal points, when only two were reported , by the square root of the product of the upper and lower CIs. For each tiny effect, we calculated the probability that the respective effect lies outside different intervals around the null: This was estimated based on the probability density function of the normal distribution, assuming each effect estimate is normally distributed on the log scale. This can be seen as a Bayesian interpretation assuming a locally uniform prior distribution. Exceedingly small, tiny or small biases, respectively, can create or destroy effects of such magnitude. P-values are two tailed. Results Eligible effect estimates Across the three literature searches, we identified articles reporting in their abstract nominally significant RR estimates between 0. After full-text evaluation of these studies, 99 effect estimates were deemed ineligible Figure 1 , whereas 51 tiny effect estimates reported in 40 articles 17â€”56 were eligible Table 1. Figure 1 View large Download slide Selection of eligible effect estimates through the three searches.

Chapter 2 : Epidemiological Practices in Research on Small Effects : Moyses Szklo :

Epidemiological Practices in Research on Small Effects by Moyses Szklo, , available at Book Depository with free delivery worldwide.

It is intended to illustrate some of the most common examples of potential study bias to help policy makers, journalists, trainees, and the public understand the strengths and weaknesses of various types of health care research and the kinds of study designs that are most trustworthy. It is neither a comprehensive guide nor a standard research methods article. The authors intend to add to these examples of bias in research designs in future brief and easy-to-understand articles designed to show both the scientific community and the broader population why caution is needed in understanding and accepting the results of research that may have profound and long-lasting effects on health policy and clinical practice. Many studies of health care effectiveness do not show the cause-and-effect relationships that they claim. They have faulty research designs. Mistaken conclusions later reported in the news media can lead to wrong-headed policies and confusion among policy makers, scientists, and the public. Unfortunately, little guidance exists to help distinguish good study designs from bad ones, the central goal of this article. There have been major reversals of study findings in recent years. Consider the risks and benefits of postmenopausal hormone replacement therapy HRT. In the s, epidemiological studies suggested higher doses of HRT might cause harm, particularly cancer of the uterus 2. In subsequent decades, new studies emphasized the many possible benefits of HRT, particularly its protective effects on heart disease â€" the leading killer of North American women. The uncritical publicity surrounding these studies was so persuasive that by the s, about half the postmenopausal women in the United States were taking HRT, and physicians were chastised for under-prescribing it. Yet in , the largest randomized controlled trial RCT of HRT among postmenopausal women found small increases in breast cancer and increased risks of heart attacks and strokes, largely offsetting any benefits such as fracture reduction 3. The reason these studies contradicted each other had less to do with the effects of HRT than the difference in study designs, particularly whether they included comparable control groups and data on preintervention trends. In the HRT case, health-conscious women who chose to take HRT for health benefits differed from those who did not â€" for reasons of choice, affordability, or pre-existing good health 4. These fundamental nuances were not reported in the news media. Another pattern in the evolution of science is that early studies of new treatments tend to show the most dramatic, positive health effects, and these effects diminish or disappear as more rigorous and larger studies are conducted 5. As these positive effects decrease, harmful side effects emerge. Yet the exaggerated early studies, which by design tend to inflate benefits and underestimate harms, have the most influence. Rigorous design is also essential for studying health policies, which essentially are huge real-world experiments 1. We know little about the risks, costs, or benefits of such policies, particularly for the poor and the sick. This article focuses on a fundamental question: That is, which study designs are most immune to the many biases and alternative explanations that may produce unreliable results 9? Our analysis is based on more than 75 years of proven research design principles in the social sciences that have been largely ignored in the health sciences 9. These simple principles show what is likely to reduce biases and systematic errors. We will describe weak and strong research designs that attempt to control for these biases. Those examples, illustrated with simple graphics, will emphasize 3 overarching principles: No study is perfect. But we will show that most problems of bias are caused by weak designs yielding exaggerated effects. We will show that such differences are often more responsible for any differences effects than is the health service or policy of interest. Publishing innovative but severely biased studies can do more harm than good. Sometimes researchers may publish overly definitive conclusions using unreliable study designs, reasoning that it is better to have unreliable data than no data at all and that the natural progression of science will eventually sort things out. We do not agree. We will show how single, flawed studies, combined with widespread news media attention and advocacy by special interests, can lead to ineffective or unsafe

policies 1. The case examples in this article describe how some of the most common biases and study designs affect research on important health policies and interventions, such as comparative effectiveness of various medical treatments, cost-containment policies, and health information technology. Generally, systematic literature reviews provide more conservative and trustworthy evidence than any single study, and conclusions of such reviews of the broad evidence will also be used to supplement the results of a strongly designed study. Finally, we illustrate the impacts of the studies on the news media, medicine, and policy. Healthy User Bias in Designs of Studies of Influenza Vaccination This case example describes healthy user bias in studies attempting to compare healthy users of influenza flu vaccines with unhealthy nonusers eg, frail, severely ill and attributing the differences to the vaccines. Flawed results of poorly designed experiments have dictated national vaccination policies. More rigorous longitudinal studies suggest that national flu vaccine campaigns have not lowered mortality rates in the elderly. Background Selection biases may be the most ubiquitous threat to the trustworthiness of health research. Selection bias occurs when differences between treatment recipients and nonrecipients or control groups based on such factors as income, race, or health may be the true cause of an observed health effect rather the treatment or policy itself. Healthy user bias is a type of selection bias that occurs when investigators fail to account for the fact that individuals who are more health conscious and actively seek treatment are generally destined to be healthier than those who do not. This difference can make it falsely appear that a drug or policy improves health when it is simply the healthy user who deserves the credit One well-known example is the national campaign in the United States to universally vaccinate all elderly people against the flu. The goal is to reduce the most devastating complications of flu, death and hospitalizations for pneumonia No one disputes the idea that flu vaccines reduce the occurrence and symptoms of flu, but the national campaign was based on the assumption that the vaccines could also reduce the number of pneumonia-related hospital admissions and deaths. This assumption was based on dozens of cohort studies that compared what happened to older patients who chose to get a flu vaccination with what happened to older patients who did not or could not. These cohort studies, however, did not account for healthy user bias. For example, a study of 3, people with pneumonia and at high risk for flu and its complications illustrated that elderly people who received a flu vaccine were more than 7 times as likely to also receive the pneumococcal vaccine as elderly people who did not receive a flu vaccine Figure 1. They were also more likely to be physically independent, have quit smoking, and to be taking statins, a medication that improves survival of patients with heart disease, diabetes, and other conditions and prevents heart attacks and strokes among the elderly In short, elderly people who got the flu vaccine already were healthier, more active, and received more treatment than those who did not and so had lower rates of flu-related hospitalization and death during the study period Healthy user bias, a type of selection bias, is demonstrated in a study of 3, patients with pneumonia and at high risk for flu and its complications , where elderly flu vaccine recipients were already healthier than nonrecipients. Figure is based on data extracted from Eurich et al Most of these interventions, when subjected to randomized trials, show no particular benefits and, sometimes, even harm. Weak research designs that do not control for healthy user bias One of the most common study designs examining the risks and benefits of drugs and other interventions is the epidemiological cohort design, which compares death and disease rates of patients who receive a treatment with the rates of patients who do not. Although seemingly straightforward, this design often fails to account for healthy user bias, especially in studies of health care benefits. For example, one of many weak cohort studies purported to show that flu vaccines reduce mortality in the elderly Figure 2. This study, which was widely reported in the news media and influenced policy, found significant differences in the rate of flu-related deaths and hospitalizations among the vaccinated elderly compared with that of their unvaccinated peers A weak cohort study comparing the risk of death or hospitalization for pneumonia or flu among vaccinated versus unvaccinated elderly: Figure is based on data extracted from Nichol et al In general, we should be skeptical about the benefits of health care interventions such as the use of drugs or vaccines reported in cohort studies. Also, the same healthier people are less likely to have side effects or quit medications.

Finally, harms and complications are far rarer than the possible benefits. Strong research designs that do control for healthy user bias Epidemiological studies that have led to national campaigns have been overturned by subsequent stronger studies. One landmark study 12 found that the fourfold increase in the percentage of elderly people in the United States receiving a flu vaccine during 3 decades â€" was accompanied not by a decrease, but an increase, in hospitalizations and deaths Figure 3 in http: This does not mean the vaccination is causing flu-related deaths or pneumonia. It means the population is getting a bit older and a bit sicker during flu season and the vaccine has little effect among the elderly. This study did not have the healthy user bias found in the previous study because it did not compare health-conscious elderly people who chose to get the flu vaccine with their sicker counterparts who chose not to. Instead, it evaluated whether a marked rise in flu vaccines resulted in fewer deaths over time in the entire population. This study, using a strong design with year trend data, demonstrates the power of pictures â€" little statistical training is needed to interpret the graph. A strong, particularly creative study published in 17 used the same epidemiological design of the weak study illustrated in Figure 2 to show that the so-called benefits of the flu vaccine were statistically equivalent before, during, and after flu season Figure 3. The cohort study compared vaccinated elderly and unvaccinated elderly. Figure is based on data extracted from Campitelli et al If fewer vaccinated elders die in the absence of the flu, it is because they are already healthier than unvaccinated elders who may be already too sick to receive a flu vaccination. Studies with strong research designs that control for selection bias and overturn the exaggerated findings of studies with weak research designs show how weak science in combination with dramatic results can influence the adoption of ineffective health policies. Certainly, greater use of flu vaccine may be reducing the incidence and symptoms of flu. However, the massive national flu vaccination campaign was predicated on reducing the number of flu-related deaths and hospitalizations for pneumonia among the elderly. It could be argued that the funds used for such a campaign could be better spent on developing more effective vaccines or treatments or other methods to reduce the spread of flu. The news media played a major role in disseminating the misleading results of studies that did not properly take into account the influence of healthy user bias in claims that flu vaccinations could reduce mortality rates and hospitalizations among the elderly. Reuters, for example Box 1 , was unequivocal in its support of a cause-and-effect relationship based on the report 15 suggesting that flu shots saved lives among the elderly. Reuters Health, October 3, Flu jab cuts illness and death in elderly In a study of relatively healthy elderly HMO members, getting a flu shot significantly reduced the odds of being hospitalized with an influenza-related ailment and of dying. Flu vaccination reduced the risk of hospitalization for pneumonia or influenza by 27 percent and reduced the risk of death by 48 percent, the report indicates. Volunteer hospitals already tend to have more experienced physicians and healthier patients, which may influence health outcomes more than the intervention does. The flawed results of these sorts of experiments led to federal health IT initiatives, resulting in trillions of dollars spent on unproven and premature adoption of the technologies and few demonstrated health benefits. RCTs failed to replicate the findings on cost savings and lives saved suggested in the poorly designed studies. Background Researchers often attempt to evaluate the effects of a health technology by comparing the health of patients whose physicians use the technology with the health of patients whose physicians do not. But if the 2 groups of physicians or hospitals are different eg, older vs younger, high volume vs low volume of services , those differences might account for the difference in patient health, not the technology being studied. Our national investment in health IT is a case in point. If physicians do not achieve this goal, they will be penalized in the form of reduced Medicare reimbursements. The program is a part of national health care reform and costs trillions of dollars in public and private funds In fact, the RAND think tank has recanted its earlier projections as being overly optimistic and based on less than adequate evidence Furthermore, recent studies and even the US Food and Drug Administration are documenting that health IT can lead to the very medical errors and injuries that it was designed to prevent 21, Figure 4 illustrates that underlying differences exist between physicians and hospitals who do or do not use EHRs 23, Large physician practices and teaching hospitals are much more likely to use EHRs than are small or solo practices or nonteaching hospitals. Because

hospital size and teaching status are predictors of quality of care with larger hospitals and teaching hospitals predicting higher quality , the 2 factors can create powerful biases that can lead to untrustworthy conclusions. Thus, although studies may associate health IT with better patient health, what they are really pointing out are the differences between older physicians and younger physicians or differences between large physician practices and small physician practices. Such large differences between EHR adopters and nonadopters make it almost impossible to determine the effects of EHRs on health in simple comparative studies. Perhaps as more hospitals adopt EHRs or risk penalties, this type of selection bias may decrease, but that is in itself a testable hypothesis.

Chapter 3 : Epidemiological practices in research on small effects.

In modern societies, epidemiology is increasingly confronted with the detection and evaluation of small risks, especially from environmental exposures and various lifestyles.

Causal inference Although epidemiology is sometimes viewed as a collection of statistical tools used to elucidate the associations of exposures to health outcomes, a deeper understanding of this science is that of discovering causal relationships. For epidemiologists, the key is in the term inference. Correlation, or at least association between two variables, is a necessary but not sufficient criteria for inference that one variable causes the other. Epidemiologists use gathered data and a broad range of biomedical and psychosocial theories in an iterative way to generate or expand theory, to test hypotheses, and to make educated, informed assertions about which relationships are causal, and about exactly how they are causal. Epidemiologists emphasize that the "one cause â€" one effect" understanding is a simplistic mis-belief. If a necessary condition can be identified and controlled e. Bradford Hill criteria[edit] Main article: Bradford Hill criteria In , Austin Bradford Hill proposed a series of considerations to help assess evidence of causation, [39] which have come to be commonly known as the " Bradford Hill criteria ". A small association does not mean that there is not a causal effect, though the larger the association, the more likely that it is causal. Consistent findings observed by different persons in different places with different samples strengthens the likelihood of an effect. Causation is likely if a very specific population at a specific site and disease with no other likely explanation. The more specific an association between a factor and an effect is, the bigger the probability of a causal relationship. The effect has to occur after the cause and if there is an expected delay between the cause and expected effect, then the effect must occur after that delay. Greater exposure should generally lead to greater incidence of the effect. However, in some cases, the mere presence of the factor can trigger the effect. In other cases, an inverse proportion is observed: A plausible mechanism between cause and effect is helpful but Hill noted that knowledge of the mechanism is limited by current knowledge. Coherence between epidemiological and laboratory findings increases the likelihood of an effect. However, Hill noted that " The effect of similar factors may be considered. This question, sometimes referred to as specific causation, is beyond the domain of the science of epidemiology. Conversely, it can be and is in some circumstances taken by US courts, in an individual case, to justify an inference that a causal association does exist, based upon a balance of probability. The subdiscipline of forensic epidemiology is directed at the investigation of specific causation of disease or injury in individuals or groups of individuals in instances in which causation is disputed or is unclear, for presentation in legal settings. Population-based health management[edit] Epidemiological practice and the results of epidemiological analysis make a significant contribution to emerging population-based health management frameworks. Population-based health management encompasses the ability to: Modern population-based health management is complex, requiring a multiple set of skills medical, political, technological, mathematical etc. This task requires the forward looking ability of modern risk management approaches that transform health risk factors, incidence, prevalence and mortality statistics derived from epidemiological analysis into management metrics that not only guide how a health system responds to current population health issues, but also how a health system can be managed to better respond to future potential population health issues. Population Life Impacts Simulations: Measurement of the future potential impact of disease upon the population with respect to new disease cases, prevalence, premature death as well as potential years of life lost from disability and death; Labour Force Life Impacts Simulations: Measurement of the future potential impact of disease upon the labour force with respect to new disease cases, prevalence, premature death and potential years of life lost from disability and death; Economic Impacts of Disease Simulations: Measurement of the future potential impact of disease upon private sector disposable income impacts wages, corporate profits, private health care costs and public sector disposable income impacts personal income tax, corporate income tax, consumption taxes, publicly funded health care costs. Applied field epidemiology[edit]

Applied epidemiology is the practice of using epidemiological methods to protect or improve the health of a population. Applied field epidemiology can include investigating communicable and non-communicable disease outbreaks, mortality and morbidity rates, and nutritional status, among other indicators of health, with the purpose of communicating the results to those who can implement appropriate policies or disease control measures. Humanitarian context[edit] As the surveillance and reporting of diseases and other health factors becomes increasingly difficult in humanitarian crisis situations, the methodologies used to report the data are compromised. One study found that less than half Among the mortality surveys, only 3. As nutritional status and mortality rates help indicate the severity of a crisis, the tracking and reporting of these health factors is crucial. Vital registries are usually the most effective ways to collect data, but in humanitarian contexts these registries can be non-existent, unreliable, or inaccessible. As such, mortality is often inaccurately measured using either prospective demographic surveillance or retrospective mortality surveys. Prospective demographic surveillance requires lots of manpower and is difficult to implement in a spread-out population. Retrospective morality surveys are prone to selection and reporting biases. Other methods are being developed, but are not common practice yet. One way to assess the validity of findings is the ratio of false-positives claimed effects that are not correct to false-negatives studies which fail to support a true effect. To take the field of genetic epidemiology, candidate-gene studies produced over false-positive findings for each false-negative. By contrast genome-wide association appear close to the reverse, with only one false positive for every or more false-negatives. By contrast other epidemiological fields have not required such rigorous reporting and are much less reliable as a result. Random error is just that: It can occur during data collection, coding, transfer, or analysis. Examples of random error include: Random error affects measurement in a transient, inconsistent manner and it is impossible to correct for random error. There is random error in all sampling procedures. This is called sampling error. Precision in epidemiological variables is a measure of random error. Precision is also inversely related to random error, so that to reduce random error is to increase precision. Confidence intervals are computed to demonstrate the precision of relative risk estimates. The narrower the confidence interval, the more precise the relative risk estimate. There are two basic ways to reduce random error in an epidemiological study. The first is to increase the sample size of the study. In other words, add more subjects to your study. The second is to reduce the variability in measurement in the study. This might be accomplished by using a more precise measuring device or by increasing the number of measurements. Note, that if sample size or number of measurements are increased, or a more precise measuring tool is purchased, the costs of the study are usually increased. There is usually an uneasy balance between the need for adequate precision and the practical issue of study cost. Systematic error[edit] A systematic error or bias occurs when there is a difference between the true value in the population and the observed value in the study from any cause other than sampling variability. An example of systematic error is if, unknown to you, the pulse oximeter you are using is set incorrectly and adds two points to the true value each time a measurement is taken. The measuring device could be precise but not accurate. Because the error happens in every instance, it is systematic. Conclusions you draw based on that data will still be incorrect. But the error can be reproduced in the future e. A mistake in coding that affects all responses for that particular question is another example of a systematic error. The validity of a study is dependent on the degree of systematic error. Validity is usually separated into two components: Internal validity is dependent on the amount of error in measurements, including exposure, disease, and the associations between these variables. Good internal validity implies a lack of error in measurement and suggests that inferences may be drawn at least as they pertain to the subjects under study. External validity pertains to the process of generalizing the findings of the study to the population from which the sample was drawn or even beyond that population to a more universal statement. This requires an understanding of which conditions are relevant or irrelevant to the generalization. Internal validity is clearly a prerequisite for external validity. Selection bias[edit] Selection bias occurs when study subjects are selected or become part of the study as a result of a third, unmeasured variable which is associated with both the exposure and outcome of interest. Sackett D cites the example of

Seltzer et al. Information bias[edit] Information bias is bias arising from systematic error in the assessment of a variable. A typical example is again provided by Sackett in his discussion of a study examining the effect of specific exposures on fetal health: Confounding[edit] Confounding has traditionally been defined as bias arising from the co-occurrence or mixing of effects of extraneous factors, referred to as confounders, with the main effect s of interest. The counterfactual or unobserved risk RA0 corresponds to the risk which would have been observed if these same individuals had been unexposed i. The true effect of exposure therefore is: Since the counterfactual risk RA0 is unobservable we approximate it using a second population B and we actually measure the following relations: Example assumes binary outcome and exposure variables. Some epidemiologists prefer to think of confounding separately from common categorizations of bias since, unlike selection and information bias, confounding stems from real causal effects. One notable undergraduate program exists at Johns Hopkins University , where students who major in public health can take graduate level courses, including epidemiology, their senior year at the Bloomberg School of Public Health. Many other graduate programs, e. Reflecting the strong historical tie between epidemiology and medicine, formal training programs may be set in either schools of public health and medical schools. Epidemiologists can also work in for-profit organizations such as pharmaceutical and medical device companies in groups such as market research or clinical development.

Chapter 4 : Epidemiological practices in research on small effects (edition) | Open Library

In this book, numerous contributions and illustrated examples show the effects of this problem, and sets out how future research should be approached in order to minimize the problems, thus producing clear results of significance.

Obesity Prevention Center OPC The University of Minnesota Obesity Prevention Center OPC provides leadership and coordination at the local, national, and international level for multidisciplinary research and education that focuses on understanding and responding to the worldwide public health crisis of epidemic excessive weight gain and obesity. The faculty and programs coordinated through OPC seek to be catalysts for interdisciplinary collaboration across the University of Minnesota, between the University and the local community, and between individuals and organizations nationally and internationally that wish to address this important public health issue. Simone French Obesity prevalence has increased during the past 30 years. Children and adolescents who are obese are very likely to be obese as adults. No effective treatments for obesity have been identified. The increases in obesity prevalence are easy to document. However, changes in the two behaviors that affect obesity, dietary intake and physical activity, have been challenging. Even more challenging has been the identification of the changes in the food and built environment that have led to excess energy intake, physical inactivity and obesity. Gaining a better understanding of the environmental variables that influence behaviors related to obesity is important to develop interventions and policies to help reverse the epidemic of obesity and its companion, Type 2 diabetes. Multiple levels of influence need to be examined, spanning from federal, state and local policies about the food and built environment, transportation policies, neighborhood social factors, including poverty, income and racial and ethnic disparities, the family home environment and parenting practices, leisure time choices and behavioral and genetic variables that might contribute to obesity risk. Research The Division of Epidemiology has a core of faculty who are internationally recognized for their research on the behavioral and environmental factors associated with obesity, and on interventions designed to prevent obesity in adult, child, and adolescent populations. Faculty expertise includes nutrition, physical activity, behavioral intervention, community intervention, environmental intervention and health policy. More generally, the University of Minnesota has a strong obesity research base in nutrition, kinesiology, psychology, clinical medicine, the basic sciences, and other supporting fields. Faculty research areas include Community-level interventions with children, families and under-represented populations low-income and minority: Environmental interventions; Economic factors that influence food purchasing and diet; food marketing and food retailing; Individual behavioral interventions focused on eating and physical activity behavior change; Mechanisms of eating and physical activity behaviors behavioral choice determinants; motivation; social influences ; Clinical intervention methods for weight loss; Genetic and biological risk factors for obesity; Inter-generational transmission of obesity risk epigenetics ; Food policies including economic factors, farm policy, federal food programs ; Transportation and built environment and policies. Five hundred families with preschool-aged children will participate in the randomized study. The study will include a family advocate who will work with each family to make changes in the home environment related to healthy food choices, reducing screen time, and increasing physical activity. In October , it was determined that there was no difference in cardiovascular events between groups and the trial was transitioned to a longitudinal observational cohort study. Jeffery is the Director of the Epidemiology and Intervention Core, which provides high quality services for epidemiological and behavioral intervention studies to other Center investigators. This project is part of a U01 mechanism and includes two phases: Lisa Harnack Funding Agency: NIH This study is evaluating whether prohibiting the purchase of foods high in discretionary calories with Supplemental Nutrition Assistance Program SNAP benefits may improve the nutritional quality of foods purchased and consumed by program participants, especially when paired with an incentive to encourage the purchase of more nutritious foods. Melissa Laska PI Funding agencies: Recent calls to action from the Institute of Medicine, the Centers for Disease Control and Prevention and other authorities

have identified improving access to healthy foods as a primary strategy for local governments to use in advancing obesity prevention efforts, but policy initiatives in this area have been limited. In this study, the impact of the Minneapolis Staple Food Ordinance will be evaluated by assessing objectively measured changes in: These changes will be assessed pre- and post-policy implementation in two Minnesota cities: Paul, our control community. The proposed scope of work in this study is important because its takes advantage of a unique opportunity to evaluate an innovative local policy addressing a recommended action area for obesity prevention that aligns with key recommendations by leading obesity prevention authorities. To our knowledge, the Minneapolis Staple Food Ordinance is the only policy of its kind in the US, and as such it could serve as an important model policy for other local governments if it is successful. Follow-up study with young adults: The EAT survey was revised based on an expanded model, integrating an ecological perspective with Social Cognitive Theory. Previous Project EAT participants were contacted by mail and asked to complete the revised survey, a dietary questionnaire. School-based study with teens: A new group of young people are being recruited from middle schools and high schools in Minnesota. This component of the study includes in-school surveys and measurements of student height and weight, as well as measurements of peer, school, and neighborhood environments. Environmental measures are being completed by peers themselves and school personnel. Jacobs, Lyn Steffen Funding Agency: The CARDIA cohort was recruited in to be balanced on gender, ethnicity, age, and educational attainment among 18 to 30 year-olds in four U. These participants have now been followed for 20 years to examine inter-relationships of the major risk factors for CHD in young adulthood as well as emerging risk factors. As the cohort enters middle age, coronary artery calcification will be measured to assess the development of subclinical atherosclerosis and its relationship with antecedent risk factor levels. These trends will help us to better understand the risk factor patterns leading to early disease in an age range when prevention is feasible. National Cancer Institute Several previous studies have shown that obese women whose body fat is greater in the abdomen than in the hips are at increased risk for diabetes, hypertension, and heart disease. This year study is determining whether body fat distribution is also related to risk of breast and endometrial cancer, and total mortality. A sample of 42, postmenopausal Iowa women completed a questionnaire and took measurements of their own bodies. The women are being followed for occurrence of cancer, using the Iowa cancer registry. Studies of diet and chronic disease occurrence also have been undertaken. Linkage to Medicare records is providing new outcome data.

Chapter 5 : Obesity Intervention & Epidemiology Research - Epidemiology & Community Health Research

*Epidemiological Practices in Research on Small Effects [Hans Hoffmeister, Moyses Szklo, Michael Thamm] on blog.quintoapp.com *FREE* shipping on qualifying offers. Epidemiology faces its limits: the search for subtle links between diet, lifestyle, or environmental factors and disease is an unending source of fear - but often yields little certainty.*

Chapter 6 : Epidemiological Practices in Research on Small Effects : Hans Hoffmeister :

Get this from a library! Epidemiological Practices in Research on Small Effects. [Hans Hoffmeister; M Szklo; Michael Thamm] -- In modern societies, epidemiology is increasingly confronted with the detection and evaluation of small risks, especially from environmental exposures and various lifestyles.

Chapter 7 : Epidemiology - Wikipedia

Contributions based on a conference held in Berlin/Potsdam from October ,

Chapter 8 : Cause and Effect in Epidemiology â€" Northwest Center for Public Health Practice

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