Methodological Innovations in Family Planning Research

by

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DISSERTATION

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UNINTENDED PREGNANCY & ABORTION:

METHODOLOGICAL INNOVATIONS IN FAMILY PLANNING RESEARCH

Heidi Serene Moseson

Abstract

Nearly half of all pregnancies worldwide are unintended (41%).[1] Among young women, this number is even higher. By the age of 20, one in three women in the United States will experience a pregnancy,[1] and over 80 percent of these will be unintended.[2,3] Ensuring that a woman is able to make the right choice for herself about whether to carry an unintended pregnancy to term is fundamental to her health and wellbeing. A woman's decision to continue or terminate an unintended pregnancy has ramifications that affect her health, her educational, professional and personal aspirations, as well as the health and wellbeing of her children. [4-7] However, methodological limitations in our ability to measure unintended pregnancy and abortion, and our ability to study their causes, limit the effectiveness of interventions designed to improve women's health.

The first chapter of my dissertation introduces a novel methodological tool for the measurement of sensitive and stigmatized events: the list experiment. Validation studies suggest that the degree of underreporting of self-reported abortions is high. In countries where abortion is illegal, underreporting may be even greater. But without accurate estimates of the size of the population affected, effective policy and programs cannot be developed or targeted. This chapter describes results from a study of women of reproductive age in Liberia in 2013. To measure abortion prevalence, each woman was read two lists: A) a list of non-sensitive items, and B) a list of correlated non-sensitive items with abortion added. The sensitive item, abortion, was randomly added to either

List A or List B for each respondent. The respondent reported a simple count of the options on each list that she had experienced, without indicating which options. Difference in means calculations between the average counts for each list were then averaged to provide an estimate of the population proportion that has had an abortion.

The second chapter of my dissertation extends the work of the first chapter. I implement two multivariable regression estimators with the list experiment data to understand how age and education vary with history of abortion. We find that education and abortion are inversely associated, after accounting for age. The hope is to encourage other epidemiologists to utilize newly developed tools for multivariable regression estimation with list experiment data.

The third and final chapter of the dissertation moves from measurement to analysis. The aim of this chapter is to introduce a causal inference framework to the family planning literature. I examine whether social support is causally linked to the incidence of undesired pregnancy among approximately 1,000 young women in Michigan. Using multivariable logistic regression, and an extension using standardization, I calculate relative and absolute estimates of the incidence of undesired pregnancy under two levels of social support.

As a body of work, my dissertation introduces a novel measurement tool to the field toward the goal of more accurate measurement – a first principle of epidemiology. It also offers a roadmap for how to approach family planning questions with a causal inference framework, to bring new rigor to the field, and improve our understandings of the complex determinants of unplanned pregnancy and abortion.

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Chapter 1: Reducing under-reporting of stigmatized health events using the List Experiment: results from a randomized, population-based study of abortion in Liberia

Heidi Moseson, Moses Massaquoi, Christine Dehlendorf, Luke Bawo, Bernice Dahn, Yah Zolia, Eric Vittinghoff, Robert A. Hiatt, and Caitlin Gerdts.

Abstract

Background: Direct measurement of sensitive health events is often limited by high levels of underreporting due to stigma and concerns about privacy. Abortion in particular is notoriously difficult to measure. This study implements a novel method to estimate the cumulative lifetime incidence of induced abortion in Liberia.

Methods: In a randomly selected sample of 3,219 women ages 15-49 years in June 2013 in Liberia, we implemented "The Double List Experiment". To measure abortion incidence, each woman was read two lists: A) a list of non-sensitive items, and B) a list of correlated non-sensitive items with abortion added. The sensitive item, abortion, was randomly added to either List A or List B for each respondent. The respondent reported a simple count of the options on each list that she had experienced, without indicating which options. Difference in means calculations between the average counts for each list were then averaged to provide an estimate of the population proportion that has had an abortion.

Results: The list experiment estimates that 32% (95%CI:0.29-0.34) of respondents surveyed had ever had an abortion (26% of women in urban areas, and 36% of women in rural areas, p-value-for-difference <0.001), with a 95% response rate.

Conclusions: The list experiment generated an estimate five times greater than the only previous representative estimate of abortion in Liberia, indicating the potential utility of this method to reduce underreporting in the measurement of abortion. The method could be widely applied to measure other stigmatized health topics, including sexual behaviors, sexual assault, or domestic violence.

Introduction

Validation studies suggest that the degree of underreporting on self-reported health exposures and outcomes can be substantial, particularly for sensitive topics in sexual and reproductive health.[1,2] This is particularly true for abortion, as indicated by studies that compare survey responses to patient medical records.[3-6] These studies find that directly asking participants about their abortion experience in contexts where abortion is legal results in underreporting of up to 70%.[7] In countries where abortion is illegal, underreporting may be even greater. Unsafe abortion contributes to maternal mortality around the world,[8] particularly in places where abortion is illegal. But without accurate estimates of the size of the population affected, effective policy and programs cannot be developed or targeted.

Alternative methods for measuring abortion aim to improve accuracy by better protecting the privacy and confidence of the respondent. Some of these methods include the random-response technique (RRT), the Anonymous Third Party Reporting (ATPR) method, the Sealed Envelope or Ballot-Box method, and various other question administration strategies.[9-16] Each of these strategies, however, has its limitations due to the time required for administration or complexity of design, and they continue to result in abortion underreporting.[12]

The list experiment is used in political science and social psychology to increase disclosure of truthful answers on sensitive subjects.[17-19] The method ensures that the interviewer cannot know whether a respondent has exhibited the behavior of interest, because the only information reported is a number. In this way, the list experiment overcomes barriers to reporting that result from women's reluctance to explicitly acknowledge having had an abortion due to the presence of shame or perceived judgment by others.[20] Also known as the "item count technique", list experiments have been used to measure illicit drug use,[17] racism,[19] risky sexual behavior,[21] drug violence and gang affiliation,[22] among other subjects. However, to the best of our knowledge, this method has not been used to measure abortion, or any health issues other than risky sexual behavior.

We tested the list experiment as a new method for measuring abortion in Liberia, a country where maternal mortality is high,[23,24] contraceptive use is low,[24] and abortion is illegal.[25] Poor access to contraceptives suggests that unintended pregnancy may be common in this setting, creating a need for abortion. We know that unsafe abortion contributes substantially to maternal mortality – 13% of maternal deaths worldwide are attributed to unsafe abortion.[26] Abortion incidence is thus likely high in contexts like Liberia, and improved data could have a large impact on improving women's health. The only previous representative estimate of abortion in Liberia is captured in the Demographic and Health Survey (DHS) data from 2007, where 6% of the female population reported having had an abortion[27] when asked directly in a face-to-face survey.[5] Given the Ebola epidemic that has overwhelmed the country's already weak health system over the past year, there is an even greater need for accurate information about women's health needs to effectively target the rebuilding of health services begun in earnest in Spring 2015.

Methods

Study Sample

This study was conducted in June and July 2013 before the Ebola epidemic by six female and six male Liberian enumerators among a representative sample of women from Liberia's capital, Monrovia, as well as from Bomi County, a neighboring rural area. Using the sample() function in the R software platform (http://www.R-project.org/), 50 enumeration areas (EAs) (2·5%) out of the 1,967 in Monrovia and 126 EAs (46%) out of the 273 in Bomi County were randomly selected with probability proportional to size. EAs are spatially defined, and were created for the 2008 National Census in Liberia.[28] Within each sampled EA, survey teams listed all households using mobile GPS-enabled maps and conversations with local residents. Starting from a random household in the EA, enumerators then selected every fourth household for interview. A household, defined as a group of individuals that eat from the same pot, was eligible if it contained at least one woman of reproductive age (15-49 years). Within each household, one woman was randomly selected for interview based on the most recent birthday.[29] Verbal informed consent was obtained from both the household head and the female respondent. The target sample size of 3,200 was arrived at based on prior conservative estimates of induced abortions in Liberia,[30] and to allow for estimation of population levels and associated characteristics within a margin of error of 10%. This study was approved by the IRBs of the Liberian Ministry of Health and the University of California, San Francisco.

Questionnaire Design & Administration

The questionnaire was designed on the Open Data Kit (ODK) platform, and assessed basic demographic characteristics including age, ethnicity, education, income, religion, marital status, and parity, followed by several embedded list experiments. The universal format of the list experiment entails a sample of respondents that is split into two groups, treatment and control. The control group is read a list of non-sensitive experiences and asked to report a count of how many of the experiences they have had, without indicating the specific events. The treatment group is read the same list of non-sensitive items, with an added sensitive item (e.g., abortion). They are similarly asked to report only how many of the events they have experienced, not which ones. Then, a difference-in-means calculation between the average numbers provided by both groups provides an estimate of the population proportion of individuals who have experienced the sensitive event.

In an effort to increase the precision of this estimate (and to better utilize the full sample), an extension to this method has been developed called the "double list experiment,"[18] which was used in this study. This method is the same as the basic method, except that there are two control lists. Both groups are asked both lists, with the sensitive item randomly added to one list for each group. Under this design, each group functions as the control for the other, and together, the two difference-in-means estimates can be averaged to provide a more precise estimate of the population proportion.[18]

The first list in the Liberia survey was a practice list asking about foods eaten in the past week to ensure respondent comprehension of the list experiment method, followed by the two abortion-specific experimental lists:

List A: "Here is a list of three things that some people have done. Please listen to them and then tell me HOW MANY you have experienced. Do not tell me which ones, just tell me how many. Here are the three things:"

1. *I have been to a prenatal ("big belly") clinic.*
2. *I have had an x-ray in a city hospital.*
3. *I have had malaria.*

"Now, how MANY of these have you experienced? None, one, two, or all?"

List B: "Now I am going to read you another list. Please listen to all of the things and then tell me HOW MANY you have done. Again, not which ones, just how many."

1. *I have taken a vaccination.*
2. *I have used an ambulance to reach the city hospital.*
3. *I have visited a health clinic.*

"Now, how MANY of these are true for you? None, one, two, or all?"

Half of the sample received the control version of List A as above, as well as a treatment version of List B with abortion ("take out belly") added as a fourth item. The other half of the sample received List B as above, and a treatment version of List A with abortion added as a fourth item. At the time each survey began, the tablet generated a random number that was then used to allocate the set of lists for that respondent. In this way, neither the researcher nor the enumerator could influence (intentionally or not) the randomization process. The expectation is that randomization of the lists will result in the balanced distribution of characteristics that could influence experience of these events – sensitive and non-sensitive alike – between the two groups.

Several design principles are important to consider in reducing the variance of the resulting population proportion estimate of induced abortion.[18] The items on the two lists were deliberately chosen to be positively correlated with one another – i.e., for any item on List A that a respondent would have experienced, there is a corresponding item on List B that would also likely be true for that respondent, or vice versa. In contrast, items within a list are negatively correlated such that it is relatively unlikely that a respondent will answer “yes” to all items (“ceiling effect”), or “no” to all items (“floor effect”).[19] This is to protect the confidentiality of the response, such that any one respondent will ideally say yes to approximately half of the list items, and therefore study personnel cannot know which specific items are true for any individual respondent. In the lists used above, items 1 and 3 in both are thought to be true of many women in Liberia, while item 2 in both lists is thought to be true for few women.[31] It is not necessary to pick non-sensitive list items with high and low prevalence – in fact, it may be preferable to avoid this given the consequent risks of ceiling or floor effects.[18] The most important considerations are the within-list negative correlation, and between-list positive correlation. However, due to the limited number of routine women’s health services offered in Liberia, the candidate list of items for each list was constrained in this study.

To provide some estimate, however imperfect, of the relative performance of the list experiment measure, a small comparison study was conducted within a sub-sample of respondents. A randomly selected sample of 600 participants was drawn from the sample of respondents who had provided their mobile number for future contact (1,548 respondents, 48% of full sample). Two study enumerators called all 600 mobile phone numbers over the course of two weeks. Each number was tried up to three times, resulting in a final comparison sample of 275 respondents (46% response) who were asked verbally, over the phone, about each of the list items individually.

Data Analysis

The lifetime cumulative incidence of abortion can be estimated for women of reproductive age in Liberia using the average of two difference-in-means calculations, one for List A and one for List B:

$\pi = (\Sigma Y_{T=1,i}) / N_1 - (\Sigma Y_{T=0,i})/ N_0$

Where π represents the proportion of the population that has experienced the sensitive event (i.e., abortion), Y is the number of items reported by each respondent, T represents the version of the list each individual received (T=1 is the treatment list, T=0 is the control list), N_1 represents the number of individuals that received the treatment version of the list, and N_0 represents the number of individuals that received the control version of the list ($N_0 = N - N_1$). A limitation of this formula is that, while unbiased, it can produce estimates that are outside of the 0 to 1 range.[18] Several alternative estimators have been developed to account for this, including a truncated estimator, a piecewise estimator, and a maximum likelihood estimator.[18,32] Each of these estimators performs differently in terms of bias and precision depending on the prevalence of the sensitive item. The confidence interval for the combined list estimate was calculated using linear mixed models with nested random effects for each level of clustering, to generate an estimate of the variability of the population parameter that accounts for the multi-stage sampling process. Differences in list estimates were also assessed by age of respondent, to generate estimates of abortion incidence by age. Only four respondents had missing data for list questions, and these were excluded from analysis. Data management and analyses were conducted in the R statistical platform and in Stata version 13.

Results

A total of 3,291 women between the ages of 15-49 years participated in the survey (1,917 rural, 1,374 urban), for a response proportion of 95%. On average, women in the sample were 30 years old, had three children, and most were married or living with a partner (Table 1). Several key demographic characteristics differed by urban and rural residents, including parity, religion, educational attainment, and relationship status (Table 1) and thus, we present results stratified by place of residence.

The list experiment difference-in-means estimates are shown in Table 2. For the entire sample, the list experiment estimates that 32% of women (95% CI: 29-34) have had an abortion at some point in their lives. (Utilizing an alternative estimator, the truncated estimator, to bound the estimate between 0 and 1, the list experiment estimate for the population changes to 32.2% - essentially unchanged.) Among urban women, this estimate is 26% (95% CI: 22-30), and among rural women it is 36% (95% CI: 32-39) (p-value for difference <0·001). For each list and for each possible number of indicated items, we report the proportion of respondents reporting at least that number in Table 3. Rows 1 and 3 state the proportion of respondents that reported each number of list items for those read the list with abortion (Row 1) and without (Row 3). Rows 2 and 4 report the proportion of respondents reporting at least that number of items for each list. For instance, 100% of respondents reported zero or more items for each list, because zero is the minimum possible. In the table for List A, in Row 2, Column 1, the number is 0·961. This means that 96·1% of respondents reported at least 1 list item as true for themselves on the list containing abortion. Row 4, Column 3 records that 10.7% of respondents reported that at least 3 items were true for them on the version of List A without abortion. If there is no underreporting, we should always observe that the proportion reporting at least x items is larger in the treatment list (row 2) than the control list (row 4). The bottom right cell in the "Sum" column reports the difference in means estimator (equivalent to that reported in Table 2). The negative number in List A, Row 5 (-0·008), suggests that some respondents may have misrepresented their answers on the "how many" questions; in other words, there may have been a small degree of underreporting on one or more list items.[18] This may imply that for some small number of respondents, adding abortion to the list caused them to claim they have not experienced one of the health events listed, when in fact they have. By summing the differences reported in Row 5 of Table 3, one arrives at the same difference-in-means estimate – albeit calculated in an arithmetically alternative manner.

When list responses were assessed by age of the respondent, the proportion of the population within each age category that is estimated to have experienced an abortion increases with each decade, from 21% among those under age 20, to 36% among those over age 40 (Table 2). Respondents in the comparison sub-sample were similar overall on measured characteristics to the full study sample, differing only in the number of children: validation participants had one additional child, on average, as compared to the full sample (Table 1). Among this sub-group, in which list questions were asked individually via telephone, 43% of women admitted to having had an abortion. When restricted to this same validation sub-group, the list experiment estimate for abortion is 40%. The non-sensitive list items performed mostly as expected, in that a large majority of women had attended a prenatal clinic (79%), had malaria (96%), been vaccinated (97%), and had visited a health clinic (90%). Similarly, fewer women had received an x-ray (20%) or used an ambulance (15%). We also observed negative correlation between responses to items within the same list, as expected.

Discussion

We found that implementing the list experiment to measure a sensitive health event, abortion, in a setting where abortion is illegal, proved feasible among a sample of 3,219 women in Liberia. Use of this method indicates that a substantial minority of women in our sample had ever had an abortion. The only prior representative estimate of abortion in Liberia was measured via face-to-face interviews with the Demographic and Health Survey, which estimated that 6% of women in Liberia have had an abortion.[27] The estimate generated from the list experiment here is an order of magnitude larger, which suggests that the method removes some of the pressure on respondents to underreport. Notably, these results are consistent with estimates the authors obtained from clinicians working in Monrovia and Bomi County health facilities. This estimate may be generalizable to similar contexts elsewhere.

Several important limitations of this study include the lack of a gold-standard reference for validation of the list results, such as comprehensive medical records. This suggests that our estimate may only represent a lower bound on the true population proportion of women who have had an abortion. Another limitation is low literacy in the population,[31] that may bias the results in unpredictable ways due to miscomprehension of the survey questions. There are also important strengths to this study. The large, randomly selected sample reduces the likelihood of chance or random error as primary determinants of the results, and increases the representativeness of the findings. The estimate that nearly one in three women in Liberia has experienced an abortion is consistent with anecdotal evidence, and further supported through a follow-up sub-sample.

In our sub-sample of participants with cell phones who could be reached to complete a phone survey, 43% reported having had an abortion when asked directly, similar to the list experiment estimate. It is notable that this is much higher than the previously obtained DHS estimate of 6%. The relative privacy and anonymity conferred by the phone modality may explain the greater willingness to report honestly. A study in the United States found that asking about abortion via telephone interview resulted in 22% increased odds of honest reporting as compared to in-person interviews.[7] Further, respondents may also have been more willing to speak honestly because of the prior face-to-face meeting with an enumerator, which could have established trust. At the time of this survey, mobile phone penetration in Liberia was estimated at 42 percent of the population.[33] As coverage increases, relying on a direct mobile phone-based methodology for asking about sensitive health experiences may become feasible. However, until then, the estimates obtained may not be representative given that women with cell phones could differ in important ways, unmeasured in this study, from the general female population. Further, the low response rate of this methodology limits its utility. Moving forward, however, validation studies comparing the accuracy of women's answers via mobile phone would improve our ability to evaluate the usefulness of this modality for abortion measurement in similar contexts.

The estimates of cumulative lifetime incidence of induced abortion suggest a need to reassess the resources currently directed toward abortion in places like Liberia. Abortion, when legal and performed with the requisite training and equipment, is safe and effective; however, when performed illegally, abortion poses serious health risks.[34] As part of the national commitment to reduce the high maternal mortality rate in Liberia,[35] particularly in the wake of the Ebola epidemic that further weakened maternal health services, greater attention and resources must be directed toward reducing unsafe abortions. Increasing access to contraception across the country could help toward this goal. Further, a reevaluation of current policy toward the training of clinicians and resources allocated to them to provide post-abortion care may be in order given the magnitude of the population affected. While this study did not ask about method of abortion, or about abortion-associated morbidity, assessing these aspects of abortion in Liberia in the future are important next steps for improving understanding of the scope of the issue, the specific health risks faced by women, and the full burden of morbidity and mortality that abortion holds in this population.

In conclusion, researchers' inability to elicit truthful answers to sensitive questions is a significant and persistent challenge in many areas of research.[18] The list experiment reduces underreporting of a sensitive experience, abortion, among a representative sample of respondents. The estimator holds promise for measuring the size of specific populations with sensitive health needs, burdens, or risk factors, and may prove useful for public health planning and resource allocation. Multivariate regression methods have recently been developed to explore how the probability of experiencing the sensitive item varies by respondent characteristics.[32] This will greatly add to the value of the list experiment as an epidemiological tool. Future work should explore the utility of this estimator across diverse public health issues and populations, from history of sexually transmitted infections, experiences with intimate partner violence or other abuse, provider and patient biases, and more, with substantive attention paid to validation of the measure.

Table 1.1 Demographic characteristics of full study sample, overall and stratified by urban or rural residence, as well as by validation sub-sample.

Characteristic	Overall (n=3,291)	Urban Sample (n=1,374)	Rural Sample (n=1,917)	Validation Sub-Sample (n=275)	T-test p-value*
Means, ±SD					
Age, in years	30±0.2	28±0.2	32±0.2	31±0.7	0.17
Parity	3±0.1	2±0.1	4±0.1	4±0.2	0.01
Persons living in household	7±0.4	7±1	7±0.1	8±0.3	0.47
Monthly Household Income, USD	$59±7	$90±16	$37±3	$52±9	0.06
Proportions, %					
Religion, %					
Muslim	28	9.5	41	27	0.27
Christian	71	90	58	67	0.19
Other	1	0.5	1	6	0.53
Education, %					
None	38	20	51	41	0.27
Some Primary	19	16	21	22	0.14
Completed Primary	16	19	14	14	0.31
Traditional Education	2	1	4	1	0.42
Some/All High or Trade School	21	36	9	14	0.10
College or University	4	8	1	1	0.09
Marital Status, %					
Single	26	37	17	21	0.70
Living with Partner	35	37	33	37	0.46
Married	32	21	40	34	0.45
Divorced/Separated	3	3	5	4	0.39
Widowed	4	2	5	4	0.99

*Validation sub-sample versus overall sample

Table 1.2 Estimators of the percent of women who have had an abortion. Results from list experiment estimators, by each list (A and B), as well as combined, and by age category. 95% Confidence Intervals are calculated using linear mixed models that account for clustering at each level of the sampling scheme.

	List A Estimate	List B Estimate	Average of Lists A & B	95% CI	N
Overall	28	35	32	29-34	3,291
Urban	24	28	26	22-30	1,374
Rural	31	40	36	32-39	1,917
By Age (in years)					
≤ 20	29	13	21	15-28	580
20-29	22	38	30	26-35	1,205
30-39	29	44	36	31-42	933
40+	33	39	36	29-43	571

Table 1.3 Detailed assessment of response proportions by number of reported items in the entire sample (urban and rural), by list.

List A

		Number of Reported Items					
Estimated Proportion	**Source**	**0**	**1**	**2**	**3**	**4**	**Sum**
Row 1	List with abortion	0.039	0.278	0.446	0.168	0.069	1.000
Row 2	Proportion at Least*	1.000	0.961	0.683	0.237	0.069	--
Row 3	List w/out abortion	0.031	0.376	0.486	0.107	0.000	1.000
Row 4	Proportion at Least*	1.000	0.969	0.593	0.107	0.000	--
Row 5	Row 2 minus Row 4	0.000	-0.008	0.090	0.130	0.069	0.281

List B

		Number of Reported Items					
Estimated Proportion	**Source**	**0**	**1**	**2**	**3**	**4**	**Sum**
Row 1	Treatment List	0.052	0.241	0.451	0.178	0.078	1.000
Row 2	Proportion at Least*	1.000	0.948	0.707	0.256	0.078	--
Row 3	Baseline List	0.055	0.358	0.484	0.103	0.000	1.000
Row 4	Proportion at Least*	1.000	0.945	0.587	0.103	0.000	--
Row 5	Row 2 minus Row 4	0.000	0.003	0.120	0.153	0.078	0.354

*Proportion reporting at least this number of items for the specified list.

Chapter 2: Multivariable analysis of list experiment data on abortion: a case study from Liberia

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Abstract

Background: The list experiment is a promising measurement tool for eliciting truthful responses to stigmatized or sensitive health behaviors. However, investigators may be hesitant to adopt the method due to previously untestable assumptions and the perceived inability to conduct multivariable analysis. With a recently developed statistical test that can detect the presence of a design effect – the absence of which is a central assumption of the list experiment method – we sought to test the validity of a list experiment conducted on self-reported abortion in Liberia. We also aim to introduce recently developed multivariable regression estimators for the analysis of list experiment data, to explore relationships between respondent characteristics and having had an abortion – an important component of understanding the experiences of women who have abortions.

Methods: To test the null hypothesis of no design effect in the Liberian list experiment data, we calculated the percentage of each respondent "type", characterized by response to the control items, and compared these percentages across treatment and control groups with a Bonferroni-adjusted alpha criterion. We then implemented two least squares and two maximum likelihood models (4 total), each representing different bias-variance trade-offs, to estimate the association between respondent characteristics and abortion.

Results: We find no clear evidence of a design effect in list experiment data from Liberia (p=0.18), affirming the first key assumption of the method. Multivariable analyses suggest a negative association between education and history of abortion. The retrospective nature of measuring lifetime experience of abortion, however, complicates

interpretation of results, as the timing and safety of a respondent's abortion may have influenced her ability to pursue an education.

Conclusion: Our work demonstrates that multivariable analyses, as well as statistical testing of a key design assumption, are possible with list experiment data, although with important limitations when considering lifetime measures. We outline how to implement this methodology with list experiment data in future research.

Introduction

Abortion is notoriously difficult to measure.[1-5] Women have reservations about reporting abortion experiences due to legal concerns and worries about privacy and stigma, resulting in under-reporting in direct surveys.[2,4] Inaccurate measurement of the incidence and prevalence of abortion limits the effectiveness of policy and program planning.

The list experiment is a promising measurement tool for eliciting truthful responses to stigmatized or sensitive health behaviors that has recently been applied to the measurement of abortion.[6,7] Originating in the 1980s, the list experiment is frequently used in the political science and economics literature, though rarely – if at all – in public health and epidemiology. The method, described in detail elsewhere, (e.g.[8-11]), is designed to protect the confidentiality of a respondent's answer to a sensitive question. In its simplest form, the list experiment works by dividing a study sample into two randomly selected groups. In the control group, the respondent is shown a list of non-sensitive beliefs or experiences, then is prompted to report how many of the items are true for him or her, but not which ones. The treatment group is shown the same list of non-sensitive items, but a sensitive item – i.e., abortion – is added. The treatment group participants are similarly asked to report how many of the items are true for them, not which ones. The difference in means between the numbers of items reported for the treatment list versus the control list is typically used as an estimate of the population proportion that has experienced the sensitive item (i.e. – abortion). The method relies on two core assumptions: first, the assumption of no design effect – that participants do not change their response to the control items based on the presence or absence of the treatment item; and second, that of no liars – that participants give a truthful answer to the sensitive item.[12]

In the first list experiment on abortion, estimates suggested that 32% (95%CI: 0.29,0.34) of women in Liberia had ever had an abortion – an estimate five times greater than the only previous representative estimate of abortion in Liberia.[6] A list experiment to measure lifetime history of abortion in the United States estimated that 22% of women in the sample had ever had an abortion, versus estimates of 18% resulting from direct questioning.[7] At least half a dozen other list experiments to measure abortion are now underway around the world.[13]

However, some family planning researchers have been hesitant to adopt the method due to an un-testable assumption of no design effect, as well as the difficulty of conducting multivariable analysis to explore factors associated with history or incidence of abortion. While stratum-specific estimates are straightforward to calculate with list experiment data, this becomes untenable as the number of covariates that must be adjusted for increases, in addition to being statistically inefficient.[14] However, recent methodological work from other disciplines has introduced a statistical test for the assumption of no design effect, as well as two multivariate regression estimators for use with list experiment data.[12,14,15] In this paper, we apply these methods and test the validity of the Liberian list experiment with this recently developed design effect test. We also conduct a multivariate analysis of the Liberian list experiment data, to demonstrate how relationships between respondent characteristics and having had an abortion can be conducted with these newly developed estimators for list experiment data.

Methods

Study sample

Using geographic information system data on spatially defined enumeration areas (EAs) developed in the 2008 National Liberian Census[16], we used an R script to randomly selected 176 EAs in Bomi (primarily rural) and Montserrado (urban) counties in Liberia with probability proportional to size. Within these EAs, women between the ages of 15 and 49 years were randomly selected within the approximately 3500 households that were themselves selected based on enumerator ordering from a random start. All women were recruited in June and July of 2013. More details on study sampling and recruitment can be found elsewhere.[6]

Ethics

This research was approved by the ethical review board of the Liberian Ministry of Health, and by the Committee on Human Research at the University of California, San Francisco.

List Experiment Design

To measure lifetime prevalence of abortion, we used a double list experiment.[8,9] In a double list experiment, the study sample is randomly split into two groups. Both groups received two control lists of non-sensitive, non-stigmatized health experiences. Abortion was randomly added to either List A or List B, and the other list was kept in its original form. Both groups received both lists, only one list containing abortion, and thus, each group serves as the "control" for the other. The estimated abortion prevalence based on each list is then averaged to arrive at a final estimate. The specific lists received by each group read as follows:

List A: 'Here is a list of three things that some people have done. Please listen to them and tell me HOW MANY you have experienced. Do not tell me which ones, just tell me how many. Here are the three things:
1. I have been to a prenatal ('big belly') clinic.
2. I have had an Xray in a city hospital.
3. I have had malaria.
Now, how MANY of these have you experienced? None, one, two, or all?

List B: 'Now I am going to read you another list. Please listen to all of the things and then tell me HOW MANY you have done. Again, not which ones, just how many.
1. I have taken a vaccination.
2. I have used an ambulance to reach the city hospital.
3. I have visited a health clinic.
Now, how MANY of these are true for you? None, one, two, or all?[6]

The response to each of these lists is a single number – the number of items that a given participant has experienced. More details on the administration of the double list experiment itself are described elsewhere.[6] For the purposes of this paper, we use data only from List A as the methods described below are designed for a single list only. For half of our sample, respondents received List A exactly as listed above, and the other half received List A with abortion added as a fourth item.

Testing for a Design Effect

A design effect exists if the expected number of control items reported depends on whether or not the list also includes the sensitive item.[12] The absence of a design effect is the first of two key assumptions required for valid estimation and inference using list experiment data.[12] As an initial diagnostic for a design effect, we first calculate the difference between the treatment and control groups in the proportions of participants with at least one positive response, and then repeat this calculation for two through the number of control items.[9] If all of these differences are positive, it is unlikely that a design effect is present.[12] But if some or all of the differences are negative, it is possible that some individuals altered their response to control items based on the presence of abortion on the list. A likelihood ratio test[12] for whether the observed pattern is due a design effect is implemented in the R list package by Blair and Imai 2010.[15]

Multivariable Regression

Of direct substantive interest to many investigators will be the potential dependence on covariates of a positive response to the sensitive item. In this analysis, we examine whether a lifetime history of abortion depends on age and education. We acknowledge that both age and education may be directly related to the safety and timing of any abortion received (the outcome), and that this limits inferences from this analysis. The primary objective of the analysis presented here, however, is to demonstrate the method of multivariate analysis, rather than to draw specific inferences from the results. To assess the question of dependence of age and education on history of abortion, we implemented nonlinear least squares and maximum likelihood estimators, both developed by Imai 2011.[14] Each approach has distinct strengths and shortcomings.

The non-linear least squares (NLS) implements the analysis in two steps.[14] The first is to model the number of control items reported as a function of covariates, using data for the control group only. Then in the second step, the parameter estimates from this model are used in modeling the response to the sensitive item (abortion) in the treatment group, given the response to the control items and covariates.[14] A special case of the NLS occurs when one assumes that the two sub-models (for control and sensitive items respectively) are both linear. Under those assumptions, the NLS simplifies to a linear model with interactions between treatment and covariates.[11,14] This model unfortunately does not constrain fitted values to the admissible range, and also requires use of methods that accommodate between-group differences in residual variance.

The second method, the maximum likelihood (ML) estimator, was developed to take fuller advantage of all of the information about the joint distribution of responses to the sensitive and control items.[14] This method uses maximum likelihood to estimate the parameters for two separate binomial models: the first for the probability of a positive response to the sensitive item (abortion), given covariates; and the second for the number of affirmative responses to the control list, given the response to the sensitive item and covariates. The complicated resulting likelihood is maximized using the expectation-maximization (EM) algorithm, treating the response to the sensitive item as partially missing data.[12,14] We consider constrained and unconstrained versions of the ML estimator. The constrained version increases efficiency by forcing the parameters of the model for the number of positive control item responses to be the same in the treated and control groups.[12] All four of these estimators are implemented in the same 'list' package in R used for assessing potential design effects.

In our application, we included age (in units of 5-years), and education, as a factor variable with four levels: no education (reference level), some or all elementary school, some or all of high school, and some or all of college. Seventy-nine women (2.4% of study sample) were excluded from analyses due to missing data on age (2 individuals) and education (an additional 77 individuals).

All annotated R code is presented in Appendix A.

Results

Overall, 3,464 women were approached, and 3,291 women (95%) gave informed consent to participate in the list experiment on abortion in Liberia. Women were 30 years old, on average, with a mean of three children, and most were in a committed relationship (Table

1). Several characteristics varied by urban versus rural residence, including parity and religion. Details of the sample have been reported elsewhere.[6]

Test for Design Effect

Table 2 shows our initial diagnostic for design effects. The treatment-control difference in the proportions with at least 1 positive response is slightly negative, consistent with a design effect. However, the likelihood ratio test is not statistically significant (p=0.18). We conclude that there is no statistical evidence for a design effect.

Multivariable Regression Outcomes

We present results from four models: linear least squares, non-linear least squares, constrained maximum likelihood and unconstrained maximum likelihood (Table 3). Results from a likelihood ratio test comparing the constrained and unconstrained models indicate that the unconstrained formulation of the relationship between covariates and abortion makes a statistically significant contribution to the model (p=0.02). All models assess the relationship between age, education and the sensitive item (abortion). Across all four models, results generally suggest an inverse association between higher educational attainment and abortion. For women with a high school education, this association excludes the null value in three of the four models. Women who have completed some or all of high school are only approximately one third as likely to report ever having had an abortion as compared to women with no education (aOR:0.32-0.42). No clear association between age and abortion, adjusting for education, is apparent. In three out of four control models, age is positively associated with report of control items, after accounting for education.

Standard errors for coefficient values are smallest in the linear least squares model, and comparable across the other three models. The precision of adjusted estimates of lifetime prevalence of abortion based on each of the four models is shown in Figure 1. The constrained maximum-likelihood model is most precise.

Discussion

We find no statistical evidence for a design effect in a list experiment conducted on abortion in Liberia, bolstering confidence in results from a method newly introduced to the public health field. Further, we demonstrate how multivariate analysis of list experiment results can be carried out, and introduce two multivariate estimators: a non-linear least squares estimator and a maximum likelihood estimator. Results from our multivariable analysis indicate that women with any education are less likely to respond affirmatively to the abortion list item than are women with no education, adjusting for age. These relationships exclude the null value for women with a high school education, in three of the four models.

In assessing evidence for a design effect, we find that one of the joint population proportions is negative. This could indicate evidence that the presence of abortion on the treatment list affected the number of control items reported. However, it could instead be caused by chance, or could be due to a lack of exchangeability between the treatment and control groups.[9] In running the statistical test proposed by Blair & Imai 2012,[12] we find no evidence to reject the null hypothesis of no design effect. However, it is important to note that this test could potentially miss a design effect if some of the effect is positive and some of the effect is negative, such that the biases cancel each other out.[12] However, we think this pattern is unlikely given the non-sensitive items.

The finding that education is negatively associated with history of abortion after accounting for age is difficult to interpret. One possible interpretation could be that women with more education are better informed about contraception and less likely to have an unwanted pregnancy in the first place, thus reducing their likelihood of having an abortion. Alternatively, due to the illegal status of abortion in Liberia, it could be that women who have abortions in Liberia tend to have unsafe abortions with high morbidity (if not mortality), which prevents them from continuing with their education. Without knowing when women had their abortions relative to their schooling, how safe those abortions were, and how this varies throughout our study sample, we cannot determine the direction of this association. This inability to identify the temporal ordering of the independent variables (age and education) and the dependent variable (abortion) underlies the guiding principle of only including variables measured pre-exposure in the model.

Consequently, investigators intent on using the list experiment to measure abortion should carefully consider the limitations of asking about lifetime history of abortion (or any sensitive health experience). Doing so will limit the utility of multivariate analysis of any resulting data. Asking instead about a more specific period of time, such as the past five years (acknowledging the larger sample size requirements), would not only allow for the estimation of abortion incidence, but would limit the bias of time-ordering in assessing multivariate relationships with participant demographic characteristics.

In terms of the specific estimators proposed, each has particular strengths and weaknesses. An advantage of the NLS estimator is that when the conditional mean functions are correctly specified, it is consistent.[14] A weakness, however, is that the linear form of the NLS estimator does not constrain fitted values to be between zero and the total number of possible items, and both the linear and non-linear forms do not make full use of the information on the joint distribution of control and sensitive item in the population, rendering it less statistically efficient than it could be.[12]

The maximum likelihood estimator, in comparison, is more efficient because it does use the full information about the joint distribution of responses to sensitive and non-sensitive items by treatment status, and it is more amenable to use with hierarchical data, when that is of interest. However, the ML estimator requires more intensive calculations.[14]

In considering the two estimators presented here, the NLS and ML, it may lead investigators to question which approach is "best". A 2011 simulation study compared the NLS and ML estimators in terms of bias, root mean square error (RMSE) and coverage of the 90% confidence interval.[14] In estimating the unadjusted population proportion with the sensitive item, both perform equally well with regard to bias and coverage, although the ML estimate exhibits smaller RMSE.[14] When looking at multivariate adjusted estimates, the ML estimator consistently produces estimates with less bias and greater precision as compared to the NLS estimator; however, performance was similar at sample sizes greater than ~3,000.[14] The overall estimate of the population proportion of women that has had an abortion is most precise in the constrained ML model – consistent with results presented elsewhere.[14]

This paper aims to introduce several important analytical tools to researchers interested in employing the list experiment to measure abortion (or other sensitive public health events or behaviors) and to provide a worked example. The methods presented here are clearly explicated in the political science literature,[12,14] but are new to a public health audience. The design effect test we discuss is crucial to assessing the validity of list experiment results, and may prove useful in interpreting results that do not match expectations. This paper demonstrates that multivariate analyses, as well as statistical testing of a key design assumption, are possible with list experiment data on abortion, although with important limitations when considering lifetime measures. We hope that the example presented here will facilitate the careful use of list experiments by others in the field, and thereby expand the suite of tools available for measurement of elusive public health populations.

Table 2.1 Demographic characteristics of study sample

Characteristic	Overall (n=3,212)
Means, ±SD	
Age, in years	30±0.2
Parity	3±0.1
Persons living in household	7±0.4
Monthly Household Income, USD	$59±7
Proportions, %	
Religion, %	
Muslim	28
Christian	71
Other	1
Education, %	
None	38
Some Primary	19
Completed Primary	16
Traditional Education	2
Some/All High School or Trade School	21
Community College or University	4
Marital Status, %	
Single	26
Living with Partner	35
Married	32
Divorced/Separated	3
Widowed	4

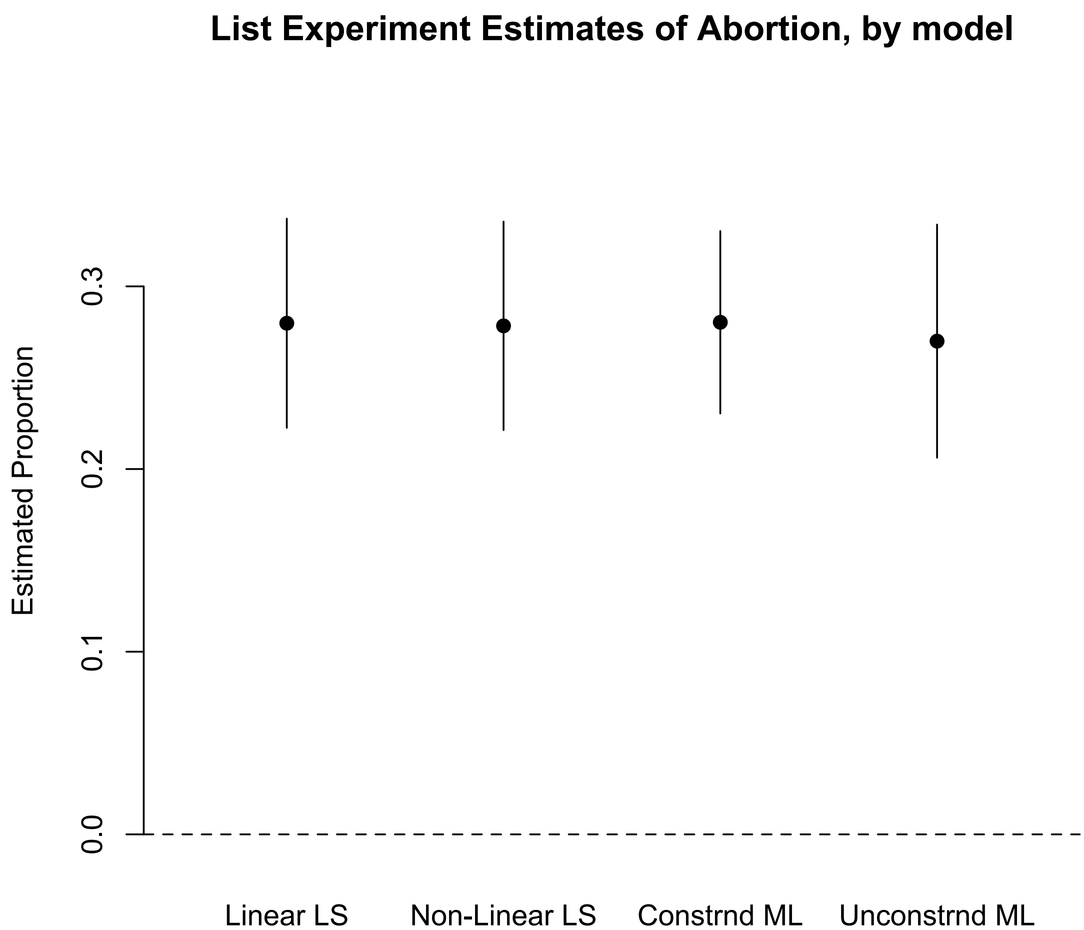
Table 2.2 Results for test of Assumption 1: No design effect.
Table contains estimates of the population proportion reporting each number of items, and at least each number of items, by treatment group. A negative proportion in the bottom row suggests that the proportion reporting at least *j* items in the treatment group is less than the proportion reporting at least *j* items in the control group (Pr(Y>=j | T=1) - Pr(Y>=j|T=0) for j = 1,…, J). (J=3, number of control item), and could be consistent with evidence for a design effect.

	Number of list items reported				
	0	**1**	**2**	**3**	**4**
Treatment list	0.040	0.278	0.446	0.168	0.068
Proportion at least	1.000	0.960	0.682	0.237	0.068
Control list	0.031	0.376	0.486	0.107	0.000
Proportion at least	1.000	0.969	0.593	0.107	0.000
Row 2 – Row 4	0.000	-0.009	0.089	0.130	0.068

Table 2.3 Estimated coefficients and odds ratios from the list experiment regression models where the sensitive item is whether or not the participant has had an abortion in her lifetime. The coefficients of interest are age and education (highlighted in grey). Standard errors and 95 percent confidence intervals are listed for the linear and non-linear models, respectively.

	Least squares estimator				Maximum Likelihood Estimator					
	Linear		Nonlinear		Constrained model		Unconstrained model			
Variables	Est.	SE	OR	95%CI	OR	95%CI	OR	95%CI	OR	95%CI
Sensitive item										
Age, 5yr increments	-0.01	0.02	0.94	(0.79, 1.12)	1.02	(0.90, 1.16)	0.80	(0.69, 0.93)		
Education										
No education	ref		ref		ref		ref			
Some or all Elementary	-0.11	0.07	0.54	(0.26, 1.09)	0.68	(0.36, 1.28)	0.71	(0.35, 1.42)		
Some or all High School	-0.17*	0.08	0.37*	(0.15, 0.90)	0.32**	(0.14, 0.73)	0.42	(0.17, 1.07)		
University/College	-0.06	0.16	0.69	(0.16, 3.01)	0.41	(0.05, 3.47)	1.87	(0.38, 9.36)		
Control items							*h0(y;x,psi0)*		*h1(y;x,psi1)*	
Age	0.03*	0.01	1.04*	(1.01, 1.06)	1.03	(1.00, 1.06)	1.01	(0.98, 1.04)	1.30***	(1.14, 1.48)
Education										
No education	ref		ref		ref		ref		ref	
Some or all Elementary	0.04	0.04	1.06	(0.94, 1.18)	1.04	(0.91, 1.18)	1.03	(0.90, 1.19)	1.10	(0.77, 1.59)
Some or all High School	-0.04	0.05	0.94	(0.83, 1.07)	0.97	(0.84, 1.12)	0.98	(0.84, 1.13)	0.81	(0.53, 1.26)
University/College	-0.01	0.09	0.99	(0.79, 1.24)	1.05	(0.80, 1.38)	1.15	(0.77, 1.69)	0.62	(0.37, 1.01)

Figure 2.1 Estimated proportion of Liberian women who have had an abortion generated from each of four models, all adjusted for age and education. The solid circle represents the point estimate for the population proportion, adjusted for age education status, and the solid lines indicate the 95% confidence intervals.



Appendix 2.1 Annotated R Code

```
# Install list package from Blair & Imai
install.packages('list')

# Load package
library('list)

# Define function for printing odds ratios for ML and NLS results
print.ors<-function(fit,ndec=2) {
 or<-round(exp(fit$par.treat),ndec)
 lb<-round(exp(fit$par.treat+qnorm(.025)*fit$se.treat),ndec)
 ub<-round(exp(fit$par.treat+qnorm(.975)*fit$se.treat),ndec)
 p.value<-round(2*pnorm(abs(fit$par.treat/fit$se.treat),lower.tail=F),4)
 cat("\nSensitive item:\n")
 print(cbind(or,lb,ub,p.value)[-1,])
 if(!is.null(fit$par.control)) {
       or<-round(exp(fit$par.control),ndec)
       lb<-round(exp(fit$par.control+qnorm(.025)*fit$se.control),ndec)
       ub<-round(exp(fit$par.control+qnorm(.975)*fit$se.control),ndec)
       p.value<-
 round(2*pnorm(abs(fit$par.control/fit$se.control),lower.tail=F),4)
       cat("\nControl item count:\n")
       print(cbind(or,lb,ub,p.value)[-1,])
 }
 else {
       or<-round(exp(fit$par.control.psi0),ndec)
       lb<-round(exp(fit$par.control.psi0+qnorm(.025)*fit$se.control.psi0),ndec)
       ub<-round(exp(fit$par.control.psi0+qnorm(.975)*fit$se.control.psi0),ndec)
       p.value<-
 round(2*pnorm(abs(fit$par.control.psi0/fit$se.control.psi0),lower.tail=F),4)
       cat("\nControl item count, negative sensitive item response:\n")
       print(cbind(or,lb,ub,p.value)[-1,])
       or<-round(exp(fit$par.control.psi1),ndec)
       lb<-round(exp(fit$par.control.psi1+qnorm(.025)*fit$se.control.psi1),ndec)
       ub<-round(exp(fit$par.control.psi1+qnorm(.975)*fit$se.control.psi1),ndec)
       p.value<-
 round(2*pnorm(abs(fit$par.control.psi1/fit$se.control.psi1),lower.tail=F),4)
       cat("\nControl item count, positive sensitive item response:\n")
       print(cbind(or,lb,ub,p.value)[-1,])
 }
}

# Define function for likelihood ratio test for comparing unconstrained and
 constrained ML fits
lrtest<-function(constrained.fit, unconstrained.fit) {
 X2<-2*abs(constrained.fit$llik-unconstrained.fit$llik)
 df<-length(unconstrained.fit$coef.names)
 lrp<-pchisq(X2,df,lower.tail=F)
 cat("\nLR test comparing constrained (ll=", constrained.fit$llik,
       ") and unconstrained (ll=", unconstrained.fit$llik, ") ML models:\n
 X2=", X2, ", df=", df, ", P=", round(lrp,4), "\n", sep="")
```

```r
}


# Load data for List Experiment analysis
load("/Users/Username/File/l1.Rdata")


# Test No Design Effect Assumption:
# l1 = dataset
# list1= list items reported by respondent
# tx1 = binary variable denoting whether individual received treatment or
 control list
# J = number of control list items
designtest<-ict.test(l1$list1, l1$tx1,J=3, gms = TRUE)
print(designtest)



# Generate estimate of population proportion based on difference in means
diff.in.means.results<-ictreg(list1~1, data=l1,treat="tx1", J=3,method='lm')
summary(diff.in.means.results)



# Linear Least Squares Estimator
lm.results<-ictreg(list1 ~ var1 + var2, data=l1, treat="tx1",J=3, method="lm")
summary(lm.results)

# Non-Linear Least Squares Estimator
nls.results<-ictreg(list1 ~ var1 + var2, data=l1, treat="tx1",J=3, method="nls")
summary(nls.results)
print.ors(nls.results)

# Constrained Maximum Likelihood Estimator
ml.cons.results<-ictreg(list1 ~ var1 + var2, data=l1, treat="tx1",J=3,
 method="ml", overdispersed=FALSE,constrained= TRUE)
summary(ml.cons.results)
print.ors(ml.cons.results)

# Unconstrained Maximum Likelihood Estimator
ml.uncons.results<-ictreg(list1 ~ var1 + var2, data=l1, treat="tx1",J=3,
 method="ml", overdispersed=FALSE,constrained=FALSE)
summary(ml.uncons.results)
print.ors(ml.uncons.results)



# Likelihood ratio test for comparison of constrained & unconstrained ML models
summary(ml.cons.results)
summary(ml.uncons.results)
lrtest(ml.cons.results,ml.uncons.results)
```

Chapter 3: No one to turn to: a causal assessment of low social support and the incidence of undesired pregnancy in Michigan

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Abstract

Background: The high incidence of unintended pregnancy in early adulthood suggests that many women experience barriers to achieving their reproductive goals. Increasingly, there is evidence to suggest that these barriers may relate directly to women's social circumstances. This analysis explores whether emotional social support is independently associated with pregnancies that are undesired at the time of conception among young women. We discuss the assumptions necessary for causal interpretation of the results, and the extent to which the analysis meets those requirements.

Methods: Using data from a prospective cohort of 970 women ages 18-20 years, we apply multivariable logistic regression to explore the association between low emotional support on the odds of undesired pregnancy over 6 months. We also use standardization to estimate adjusted absolute risk of undesired pregnancy and risk differences according to level of social support.

Results: Among white women, those who report low emotional support have nearly 7 times the odds of an undesired pregnancy over 6 months as compared to white women who reported higher emotional support (aOR: 6.77, 95%CI: 1.68, 27.13). No association was found between low social support and undesired pregnancy among young black women. Standardized estimates suggest that low social support could cause anywhere from a 9% reduction to a 26% increase in undesired pregnancies over 6 months - but all difference estimates fail to exclude the null value of 0% change.

Conclusion: Findings from this study suggest a link between undesired pregnancy in early adulthood and an upstream determinant, emotional social support. Given the persistently high incidence of unplanned pregnancy in the United States, future work should be designed to test this relationship explicitly. While the “messiness” and complexity of social exposures can be a deterrent to quantitative researchers, this paper demonstrates that even exploratory research can be illuminating in helping to guide our thinking, and to prioritize further research and public health interventions.

Introduction

By the age of 20, one in three women in the United States will experience at least one pregnancy,[1] and over 80 percent of these will be unintended.[2,3] The vast majority of unintended pregnancies in the United States are associated with inconsistent or incorrect use of contraceptives (41% of unintended pregnancies), or to a lack of contraceptive use (54% of unintended pregnancies).[4] A continuing focus of study is why women – young women in particular - are not using contraception consistently, or correctly. Partial explanations include lack of access, physical concerns about side effects, method dissatisfaction, misconceptions about fertility risk [5-7] difficulty negotiating use with a partner, ambivalence about pregnancy, and substance use.[8,9]

Drawing on research that posits that differences in the risk of early pregnancy across demographic groups reflect social, rather than biological or other, disadvantage,[10] we explore the role of emotional social support in the risk of undesired pregnancy. Our focus on undesired, rather than unintended pregnancy, reflects the ongoing evolution of the understanding of women's feelings about pregnancy.[11] While an "unintended" pregnancy is defined in terms of a woman's explicit fertility plans at the time of conception, an alternative framework exists that focuses not only planning, but rather on a woman's desire for (positive), and desire to avoid (negative), pregnancy.[12-14] In one of the few studies that has followed young women longitudinally to capture the incidence of pregnancy in early adulthood, the Relationship Dynamics and Social Life study (RDSL), investigators opted to measure pregnancy status in terms of young women's desires for pregnancy, rather than in terms of timing-based intentions, in an attempt to better capture the complex and dynamic nature of fertility hopes in the transition to adulthood.[15]

Emotional support, one of the four key dimensions of social support, is defined as "the availability of one or more persons who can listen sympathetically when an individual is having problems and can provide indications of caring and acceptance."[16] Supportive networks have been shown elsewhere to facilitate preventive health behaviors.[16-18] Several previous studies have found a positive association between social support, conceptualized in a variety of ways, and contraceptive use.[19-23] Two studies, one in Cambodia and the other in the United States, found strong cross-sectional associations between perceptions of partner support for contraceptive use, and use of a modern contraceptive method.[19,23] In an analysis of 500 women in Cameroon, women who had been encouraged by network members to use contraception were 16 times more likely to be using a modern method of contraception than women who had not.[21] Similarly, in a study of nearly 700 women in Bangladesh, the perception of immediate network members' positive attitudes toward contraception was a strong predictor of current contraceptive use.[22] Another study in Bangladesh randomized a social support intervention to assess its impact on use of modern contraceptive methods over two years.[20] Field workers met monthly with women one-on-one in their homes to discuss contraceptive methods, or organized group discussions of contraception in the homes of community thought leaders. Two years later, women in the intervention group who had been using traditional methods were three times as likely to be using modern contraception as opposed to women in the control group, and for those women already using a modern method of contraception at baseline, they were seven times more likely to still be using a modern method two years later than were women in the control group.[20]

While this prior research focused largely on normative and perceived social support for contraceptive use, we extend this research to explore whether perceived emotional social support is associated with undesired pregnancy among young women, ages 18-22, in the United States. We hypothesize that the incidence of undesired pregnancy over 6 months will be higher for young women who report lower emotional support at baseline as compared to women who report more support. A more emotionally supportive social network may increase a young woman's sense of confidence and self-worth, which may empower and enable her to seek reproductive health information and to act on it, thereby decreasing her risk of undesired pregnancy.

In this study we are interested in the potentially causal relationship of low social support to undesired pregnancy. Much reproductive health research, such as surveillance of important reproductive health indicators, does not rely on causal inference, nor should it. At the same time, much research in the reproductive health field presents associational analyses and discusses the implications as if the research were causal, when the requisite assumptions for causal inference have not been met, or even discussed.[24] There is a need to introduce a more rigorous causal inference framework, and more nuanced causal interpretation, to the family planning field, to elevate the quality and usefulness of our research. We aim to do so with this paper.

Methods

Sample and Procedures

We analyze data from the Relationship Dynamics and Social Life (RDSL) Study, a population-based study of 1,003 young women in Michigan that was designed to prospectively investigate the influence of behavioral, attitudinal and contextual aspects of relationships, contraceptive use, and activities that compete with childbearing, on the occurrence of undesired pregnancy during the transition to adulthood. The RDSL study focuses on women ages 18 to 22 years because these ages are characterized by the highest rates of undesired pregnancy, as well as significant instability and change in the dynamic determinants of undesired pregnancy. An initial 60-minute face-to-face interview was conducted with each participant to assess important aspects of her family background; demographic information; key attitudes, values, and beliefs; current and past friendship and romantic relationships; education; and career trajectories. Following the baseline interview, women participated in a weekly survey-based study. The weekly surveys captured information on rapidly changing aspects of subjects' lives, including attitudinal and behavioral measures of pregnancy, relationships and contraceptive use. The weekly surveys were completed via the Internet or over the phone. Extensive steps were taken to reduce non-response and attrition within the weekly study, including innovative reminders, incentives, and sharing of study results. More details on study design and implementation can be found elsewhere.

Of the 1,003 respondents who completed the baseline interview, 99% (n=992) agreed to enroll in the weekly journal portion of the study. Twenty-two individuals were excluded from this analysis due to missing data for exposure, resulting in an analysis dataset of n=970. By the end of the first 6 months, 84 percent of baseline participants were still enrolled in the study.

Ethics

This study was approved by the Institutional Review Boards of the University of Michigan (study #: HUM00014150) and the University of California, San Francisco (study #: 14-13501).

Measures

The exposure, perceived emotional social support, was measured at study baseline when participants were asked*: "How often do you feel that there are people you can turn to? Would you say never, almost never, sometimes, fairly often, or very often?"* We selected this measure of *perceived* emotional social support rather than *received* emotional social support, as the literature suggests that perceived measures are more predictive of health advantage than are measures of support actually received.[25,26] To facilitate translation of results, we collapsed these responses into a binary indicator of low social support – positive for those women reporting "never" or "almost never" having someone they can turn to, and negative for those reporting "sometimes", "fairly often" or "very often".

The outcome, undesired pregnancy, was defined using a combination of women's prospective responses to the positive and negative desire for pregnancy scales asked at baseline and each week thereafter. The positive scale asks: *"How much do you want to get pregnant during the next month? Please give a number between 0 and 5, where 0 means you don't at all want to get pregnant and 5 means you really want to get pregnant."* The corresponding negative scale asks: *"How much do you want to avoid getting pregnant during the next month? Please give a number between 0 and 5, where 0 means you don't at all want to avoid getting pregnant and 5 means you really want to* *avoid getting pregnant."* We created a binary indicator for undesired pregnancy that flagged a pregnancy as undesired if a woman responded between 0 and 2 on the positive desire to get pregnant and between 3 and 5 on the negative scale. We use women's responses to these scales from the week in which the pregnancy was conceived.

To mitigate confounding influences on the relationship of interest, models included the following variables: race, age, childhood family structure, employment, education, and relationship status. All variables were measured at baseline. Respondent age was included as a continuous variable. Race was included as a dichotomous indicator for black versus non-black. Several Latina women are included in both groups, although due to low numbers, were not included as a separate category. Enrolled in school and employed are both dichotomous indicators for whether the respondent was enrolled in school or employed at baseline. Relationship status was also included as a dichotomous indicator for whether or not the respondent reporting being in any kind of physical or emotional relationship at baseline. Finally, childhood family structure was included as dichotomous variable reflecting whether the respondent grew up with two parents in the household versus any other arrangement.

Analyses

All analyses were conducted in Stata version 14.2. We describe sample characteristics overall and stratified by level of emotional social support, and assess balance using t and chi-square tests as appropriate.

To assess the relationship between low emotional social support and the incidence of undesired pregnancy among young women, we conducted a logistic regression analysis to generate relative estimates of the odds of undesired pregnancy. We tested for non-linearity of age, our only continuous covariate, and found no evidence for this. The other covariables were treated as binary. We checked for omitted interactions, particularly between exposure and confounders, using Wald tests. The extent of model misspecification was assessed with the Hosmer-Lemeshow and Pearson-Windmeijer tests. Covariates were selected for inclusion based on *a priori* beliefs about their confounding influence on the relationship between exposure and outcome, identified with the aid of directed acyclic graphs (DAGs). The final model includes low emotional social support as a binary exposure, and adjusts for age, childhood family structure, employment, education, and relationship status, with an interaction between race and low emotional social support.

In a final step, we used potential outcomes estimation (POE) to estimate adjusted absolute risk of undesired pregnancy and risk differences according to level of social support (as opposed to the relative estimates generated by the multivariable logistic model described above). Potential outcomes estimation, or standardization, is motivated by the fundamental problem of causal inference: that we only get to observe one exposure and one outcome combination for each individual.[27] The method can be used to generate causal effect estimates using observational data, and proceeds in several steps: first, develop a correctly specified model for the effect of exposure (emotional support) on outcome (undesired pregnancy), conditional on confounders (age, age, childhood family structure, employment, education, and relationship status); (2) impute predicted outcome values for each exposure level, conditional on confounders; and (3) calculate the overall average treatment effect estimate by standardizing the mean outcome for each exposure group to the overall distribution of the confounders.

In its most basic sense, POE generates two duplicate datasets where the only difference between the two is exposure status: in one, everyone is set to “exposed”, and in the other, all are set to “unexposed”. Using these two counterfactual datasets with imputed outcome values, we estimate the percent of young women that would have an undesired pregnancy if everyone were exposed to low social support, versus the percent of young women that would have an undesired pregnancy if no one were exposed to low social support. Assuming the key assumptions of exchangeability, positivity and consistency are met, the difference in these two values gives us a causal estimate of the percent of undesired pregnancies attributable to low emotional social support in this population, commonly referred to as the average treatment effect (ATE). Stata’s margins command generates a 95% confidence interval for this estimate as well.

Sensitivity Analyses

Given the small number of undesired pregnancies in this dataset (n=30), our final logistic model violates the standard rule of thumb of having at least 10 outcomes per predictor. Thus, we ran a more parsimonious model with only the two strongest confounders (race and relationship status) as a check. We also ran this more parsimonious model using exact logistic regression to further test the robustness of results. To assess the extent to which our cut-offs for “low” emotional social support, as well as for “undesired” pregnancies affected the results – we ran our final model several times using more flexible definitions for exposure and outcome. First, we ran a model with exposure categorized in five levels as “never”, “almost never”, “sometimes”, “fairly often” and “very often” for frequency of emotional support. Similarly, we ran our final model with both a more and less strict definition of our outcome, undesired pregnancy. In another sensitivity analysis, we ran a Cox model to account for time to undesired pregnancy, as opposed to a logistic model.

Results

Sample Characteristics

At study baseline, the mean age was 19.2 years, with all participants ranging between 18-20 years of age. Thirty-three percent of young women identified as black, and the rest were primarily white (Table 1). Approximately half of respondents grew up in a two-parent household, and half were currently employed. Most women, approximately 70 percent, were enrolled in school. The majority of women (73%) were in some type of heterosexual relationship at baseline. The distribution of key confounders was well balanced across exposure groups, with the exception of race and enrollment in school (Table 1).

Low Emotional Social Support & Undesired Pregnancies

In the first six months of the RDSL study, 62 young women reported 65 pregnancies (3 women reported 2 pregnancies in this period). Of these pregnancies, 46 were reported to end in live birth (66%), 7 in abortion (11%), 8 in miscarriage or ectopic pregnancy (12%), and 7 of the pregnancies (11%) were ongoing at study end. Among these 65 pregnancies, 30 (46%) were classified as undesired (Table 2). At study baseline, 51 young women (5%) reported never or almost never having someone to whom they could turn. Among these 51 young women that reported low emotional support, 4 (8%) reported an undesired pregnancy in the first 6 months of the study, while 26 (3%) of the young women who reported higher levels of emotional support reported an undesired pregnancy in this time period.

Multivariable Logistic Model

Due to an interaction detected between emotional support and race, we present all results stratified by race. Among white women, those who reported lower emotional support had more than six times the odds of an undesired pregnancy over 6 months as compared to white women who reported higher emotional support (aOR: 6.77, 95%CI: 1.68, 27.13) (Table 2). In contrast, we found no association between emotional support and undesired pregnancy among black women (aOR: 0.64, 95%CI: 0.1, 5.1; p for interaction=0.06). Among women who reported higher emotional support, the odds of an undesired pregnancy for black women were nearly three times that for white women (aOR: 2.76, 95%CI: 1.2, 6.5). In addition, being in any kind of relationship at study baseline was strongly associated with odds of undesired pregnancy (aOR: 10.7, 95%CI: 1.4, 79.7).

Absolute risk of undesired pregnancy

Standardization results suggest that if all women in the sample were to have low social support (never or almost never having someone they can turn to), we would expect to see a cumulative incidence of unintended pregnancy of 8.1% over 6 months (Table 3). In contrast, if all women had had more frequent emotional social support, we would expect to see a risk of unintended pregnancy of 2.9% over those same 6 months. Thus, assuming no unmeasured or residual confounding and correct model fit, improving young women's access to emotional social support could reduce the average risk of unintended pregnancy by 5.2% over 6 months (95%CI: -0.3%, 13.3%).

When we stratified by race, the average treatment effect of low emotional support on absolute risk of undesired pregnancy among black women suggests that low emotional support may reduce the incidence of undesired pregnancy by 2%, but did not reach statistical significance (95%CI: - 8.7%, 5.1%). Among white women, low social support may conversely increase the incidence of undesired pregnancy by nearly 11%, but this too was not statistically significant (95%CI: -3.9, 25.5).

Sensitivity Analyses

The association between emotional support, race and undesired pregnancy were robust across sensitivity analyses, although of varying magnitude and precision. Results from the exact logistic regression, controlling for race and relationship status, suggest that young white women with low emotional social support have 7.34 times the odds of undesired pregnancy over 6 months as do young white women with higher emotional social support (95%CI: 1.2, 31.4).

Discussion

In this exploratory study, we find that low emotional social support is strongly associated with the occurrence of undesired pregnancy over 6 months among young white women. No association was found among young black women. Our analysis exploring the absolute risk difference in undesired pregnancy by perceived emotional support was inconclusive. All estimates of the average treatment effect – overall and stratified by race – failed to exclude the null value of 0% change in cumulative incidence of undesired pregnancy over 6 months.

While we have not been able to identify any prior work on emotional social support and undesired pregnancy, there is prior evidence to suggest that social support, narrowly defined as normative or operational support for use of contraceptives, can influence contraceptive use,[19-23] which could plausibly impact incidence of undesired pregnancy. One possible mechanism, supported by the theoretical literature, suggests that emotional support may operate by enhancing individual self-esteem and coping abilities, thereby enabling individuals to take preventative health steps.[16] In this context, this may indicate that young women with emotional support may be empowered to obtain contraceptives and/or negotiate their use with a partner, decreasing their risk of undesired pregnancy. For those women with low emotional support, it is possible that they may be more open to an undesired pregnancy because of the opportunity for love, care and attention that a pregnancy and baby would bring from friends and family[28] – emotional support that they lack, and perhaps desire, at the time of conception.

Our results also indicate a clear interaction between race and emotional social support. Racial differences in the influence of social support have been documented elsewhere in the reproductive health literature. One study of the influence of social support on smoking during pregnancy found that white women responded to "belonging" elements of a social support network, while black women responded to "material" elements.[29] The authors interpreted the findings to mean that tangible social support had much more of an impact for black women, while the more emotional, perceived availability of others with which to share experiences was more consequential for white women. Given that our exposure is emotional support, these findings may partially explain why we see a relationship among white women, but not among black women.

Other studies have found similar results where an interaction between race and social support reveals a strong association between whites and the outcome of interest, but not among blacks.[30] Some investigators posit that this paradox could be explained by the reality that blacks are disproportionately represented in low socioeconomic strata, are more likely to be discriminated against, and thus to experience chronic stressors.[30-32] The authors hypothesize that if blacks are more likely than whites to experience these constant stressors, the mitigating influence of social support, on average, may not be enough to overcome these obstacles.[30] In the context of family planning, these stressors could include lack of access to family planning services, mistrust in and mistreatment by health care providers, and poor quality sex education.[33,34] Due to the limited number of undesired pregnancies among black women in this study, additional work with a larger sample size and more detailed exposure measure are necessary to further explore this hypothesis.

As will all research, this study is limited by a number of factors. While the RDSL study is the largest and most comprehensive dataset available in which to investigate the relationship between emotional social support and undesired pregnancy in early adulthood, the limitations of this analysis stem, for the most part, from the fact that this question was not a primary research focus for the larger RDSL study. Further, to the best of our knowledge, no psychometric data on the reliability of our measure of emotional social support has been reported. Depending on its sensitivity and specificity in classifying individuals with low social support, our results could be biased either towards or away from the null. However, similar unidimensional scales of emotional social support have demonstrated utility in some types of epidemiologic research in samples of

800 to 2,300 subjects, comparable to our sample.[16,35] Similarly, the measurement of undesired pregnancy is a relatively new measure that does not capture all elements of women's attitudes towards pregnancy, and its relationship to post-conception acceptability of a pregnancy is unknown. If either the exposure or the outcome measures perform differently in different racial/ethnic groups, this could also be one factor contributing to the interaction we see by race/ethnicity in our analysis.

An additional limitation of our exposure measurement is that we do not have time-updated measures. In an attempt to limit the bias induced by change in exposure over time, we have restricted our analysis to only the first 6 months of over 2.5 years of data. It is possible that emotional social support may have changed during these 6 months; however, we have no reason to believe that such a change in exposure would have differed systematically by baseline exposure status. Thus, any misclassification would likely be non-differential and thereby conservatively bias results toward the null.

In addition to exploring a potential determinant of undesired pregnancy, a secondary aim of this paper is to examine the conditions under which analyses can be causally interpreted. The results presented here can only be interpreted as causal if we assume that there is no unmeasured confounding of our exposure and outcome, and that all measured confounders are also measured correctly. Given the dichotomous nature of the variables, it is possible that there is residual confounding within categories. Assuming this misclassification is non-differential, it should induce a conservative bias. The analysis is strengthened, however, by covariates that are well balanced over exposure status - meeting the positivity assumption required for causal interpretation. Causal interpretation also requires that there should only be one mechanism by which exposure influences the outcome (consistency assumption). Yet, with our exposure – a social exposure – this is unlikely to be true. It is not difficult to imagine several possible ways in which emotional support could influence a young woman's risk of undesired pregnancy. This complicates efforts to design and test an intervention to improve emotional support, as any emotional support intervention designed in a public health setting could differ in important ways from naturally occurring emotional support – and consequently have different effects on incidence of undesired pregnancy.

Despite these limitations, this analysis has many strengths, including the use of an immediately pre-conception measure of pregnancy desires and being the first study, to our knowledge, to prospectively measure emotional support and desire for pregnancy among young women over many months. Findings from this study suggest a link between undesired pregnancy in early adulthood and an upstream determinant, emotional social support. Given the persistently high incidence of unplanned pregnancy among young women in the United States and a stated goal in reducing its occurrence, future work should be designed to test this relationship explicitly. We believe this assessment of a complex, social exposure in an analysis of a fundamentally important public health outcome, early undesired pregnancy, offers a contribution to the family planning literature. While the "messiness" and complexity of social exposures can be a deterrent to quantitative researchers, this paper demonstrates that even exploratory research can be illuminating in helping to guide our thinking, and to prioritize further research and public health interventions.

Table 3.1 Individual characteristics overall and by study group.

Individual Measures, N(%)	Overall (N=970)	Low Emotional Support (N=51)	Higher Emotional Support (N=919)	P-Value for difference
Age				0.86
18 years	393 (41)	17 (33)	376 (41)	
19 years	485 (50)	33 (65)	452 (49)	
20 years	92 (9)	1 (3)	91 (10)	
Black	324 (33)	25 (49)	299 (33)	0.02*
Non-Black	646 (67)	26 (51)	620 (67)	
Grew up with two parents (both bio or bio/step)	511 (53)	23 (45)	488 (53)	0.27
Currently enrolled in school	676 (70)	27 (53)	649 (71)	0.01**
Currently employed	486 (50)	23 (45)	463 (50)	0.46
In relationship	711 (73)	43 (84)	668 (73)	0.07

Table 3.2 Women reporting an undesired pregnancy in the first 6 months post-baseline: adjusted coefficients from a multivariable logistic model (n=970)

	Adjusted Odds Ratio	**95% CI**
Low emotional support (ref: higher support)	6.78**	1.68, 27.31
Race/ethnicity (ref: white)		
Black	2.76*	1.18, 6.50
Interaction term		
Black x Low emotional support	0.089	0.01, 1.09
Age, yrs	0.94	0.48, 1.83
Childhood Family Structure (ref: less than 2 parent home)	0.86	0.39, 1.92
Currently enrolled in school	0.80	0.37, 1.75
Currently employed	0.91	0.42, 1.98
In heterosexual relationship	10.72*	1.44, 79.68

*p≤0.05
**p≤0.01

Table 3.3 Cumulative incidence of undesired pregnancy overall, and by race/ethnicity under low and non-low emotional social support.

	Emotional Support			
	Low	**Higher**	**Avg Treatment Effect**	**95%CI**
Overall	8.1%	2.9%	5.2%	(-2.8, 13.3)
Black women	3.3%	5.1%	-1.8%	(-8.7, 5.1)
White women	13.3%	2.5%	10.8%	(-3.9, 25.5)

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