Do Maps Matter in Aid Allocation Decisions?

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Abstract

Researchers believe that seeing information on aid projects and development indicators, like poverty, presented in the form of a map will lead policymakers to allocate aid most efficiently. Using a randomized online experiment, we investigated the effect of data presentation on aid allocation decisions. In addition, we also explored the extent to which study participants are influenced by biased information in their decision making calculus. We hypothesized that seeing data presented in the form of a map will lead to better decisions than if data is presented in the form of a spreadsheet or dense document. Additionally, we hypothesized that the inclusion of biased information with correct factual information will result in inefficient aid allocation decisions. Participants were randomly assigned to groups receiving varying presentations of historical aid information: a long, detailed document that includes information about each district in Malawi (document group), a map with geocoded information and a detailed document (map group), or a spreadsheet containing data and detailed document (spreadsheet group). In addition, each of these groups was randomly assigned detailed documents that included biased emotional stories. Participants were given a specific goal and were asked to decide how to allocate aid based on the information that is provided. Preliminary results suggest that participants in the map group performed better than others and participants seeing emotional stories in their documents made worse allocation decisions than others.

Introduction

Until relatively recently, donors and recipients of aid could not reliably pinpoint the exact locations of where their aid was going. In Summer 2010, a small team of students came together and set out to do what had previously been said to be too complicated, too expensive, and too time consuming. These students put the World Bank's entire active project portfolio on the map: 30,000 locations were determined for 2,500 projects in 144 countries. AidData (among many other stakeholders) felt that being able to see this georeferenced information on a map would be valuable. The ability to look at project locations alongside subnational data, such as poverty rates by district, should theoretically lead to more efficient allocation of aid.

In Summer 2011, AidData partnered with the University of Texas at Austin and the Ministry of Finance of Malawi to attempt to take aid mapping a step further. This time, the objective was to geocode the entire universe of aid in a single country. This was another revolutionary accomplishment, as it was the first time that every single aid project in a country could be pinpointed on a map. For Malawi, this meant that around 550 projects from a variety of donors totaling over $5.3 billion could be viewed spatially for the first time.

The open data movement has catalyzed wide-ranging transparency reforms within donor agencies and unlocked vast stores of data. However, making sense of this data deluge poses a major challenge for development policymakers and practitioners: evidence-based decisions require that data be made available in an easily understandable and usable format. To this end, AidData has begun to visualize geocoded aid and development data in high-resolution maps. Many other organizations from around the world are also investing significant time, money, and effort into mapping subnational aid and development data. These efforts allow the public to more easily learn where, how, and by whom aid is being spent. Conventional wisdom tells us that having this geocoded aid information should lead to more efficient allocations of aid, but this assumption has never been empirically tested.

With this paper, we hope to answer two research questions:

(1) Do study participants make better aid allocation decisions (i.e., maximize stated aid allocation goal) when presented with a map, instead of an excel spreadsheet or long word document?

(2) When presented with biased information, in addition to correct factual information, do study participants make worse aid allocation decisions (i.e., unable to maximize stated aid allocation goal or shift allocation toward the source of the bias)?

Literature Review

Evidence-based decision-making requires both accessible and comprehensible information. Once information is available, its uptake and application by decision-makers are key. The optimal methods of information communication to support decision-making is the subject of a substantial body of research in a variety of fields and settings. Of particular interest for this study is the use of visual representations. Larkin and Simon (1987) point out the differences between sequential representations of information, such as those found in text, and visual diagrammatic representations. The latter has the advantage of making explicit information that has to be extracted from sequential representations, often with great effort, and physically placing related pieces of information in close proximity. Both characteristics can reduce the effort required for comprehension.

Wickens and Carswell (1995) add that graphical visualizations specifically can lower the cognitive cost of acquiring information by shifting some tasks to a person's visual perception system. Graphs can help to improve decision-making if cognitive capacity is then applied to other aspects of the problem-solving process, which is more likely for more complex decisions (Lohse 1997). Vessey (1991) clarifies that graphic representations, which present information spatially, are most likely to improve decision-making performance when used for visual or spatial tasks and with appropriate problem-solving processes.

Decisions regarding the allocation of foreign aid are indeed complex and require decision-makers to absorb and analyze a large amount of information to identify a spatial solution (i.e. where aid should be distributed). To optimize allocation, decision-makers need to know which populations are in the greatest need, what areas have received the most aid in previous years, what types of interventions have seen the most success, and what projects are currently being undertaken by other actors. Without this information, aid allocation decisions may divert aid from the people that need it most, create duplication and inefficiencies, and impede development impact. Without such information, one might expect even the most well-intended actor to make suboptimal allocation decisions (Casamatta and Vellutini 2006).

Despite the cognitive complexity of aid allocation decisions, to date no studies have been performed on the comparative advantages of different forms of information presentation, particularly visual support tools, for such resource allocation decisions. Within the medical field, however, different visual representations of the same information have been shown to affect information interpretation and decision-making accuracy. Elting and Bodey (1991) test four representations of time-dependent information from clinical trials: narrative text, table, pie chart, and icon. They find that the speed and accuracy of information absorption is highest when medical personnel use the icon representation, and the effect is strongest during the first exposure to the information. Elting et al. (1999) also find that physicians' decisions to stop clinical trials are more accurate when using icon displays as compared to tables, pie charts, and bar graphs. The format of graphical representations even influences medical patients' understanding of and decisions regarding treatment risks (Ancker et al. 2006, Garcia-Retamero and Galesic 2013). The identification of the effects of different representations of information on aid allocation decisions has implications for increasing aid effectiveness.

Information necessary for aid allocation is often presented in extensive documents or spreadsheets. As more subnational aid information becomes available, maps are an obvious data visualization format for aid allocation decisions. Research surrounding the impact of map visualizations on spatial decision-making more broadly highlights their potential benefits in supporting complex aid allocation decisions. In order to achieve accuracy in complex decisions with high stakes, individuals and groups must undertake sophisticated analysis that weighs multiple criteria. Maps can help users consider multiple decision criteria in the same visual space to more effectively order decision options (Jankowski et al. 2001). Geographic Information Systems (GIS) and mapping are regularly used to evaluate various locational decisions with complex criteria (Malczewski 1999, Malczewski 2006). Factors that influence the effectiveness and value of spatial decision-making include the decision-making style (Andrienko, Andrienko, and Jankowski 2003), the stage of the decision-making process (Jankowski and Nyerges 2001), and whether the decision is made by an individual or a group (Malczewski 2006). The formatting choices for a map or any type of visual representation have the potential to introduce certain biases into the decision-making process (Jarvenpaa 1990, Glazer et al. 1992). While the effect of variations to a visualization on allocation decisions is not the focus of this experiment, it does present an interesting area of further research.

The determination of the impact of information presentation on aid allocation decisions requires a measure of optimal aid allocation for comparison. Collier and Dollar (2002) derived a "poverty-efficient" aid allocation formula for aid to countries taking into account several factors: per capita income, total amount of aid, poverty headcount, elasticity of poverty reduction with respect to income, population, and policy. The amount of complex measures that must be considered to determine a "poverty-efficient" level of aid make such a calculation difficult, especially when extending to the subnational level, and reinforce the potential impact of varying the presentation of relevant information.

There is evidence that greater aid transparency has increased our knowledge about the allocation (Cogneau and Naudet 2007, Svensson 2003, Collier and Dollar 2002, Alesina and Dollar 2000) and effectiveness (Christensen 2011, Nielsen et al. 2011, Findley and Young 2011, Tierney et al. 2011, Roberts et al. 2008, Casamatta and Vellutini 2006, Kosack 2003, Burnside and Dollar 2000, Boone 1996) of foreign aid. Yet the question of how to present aid and development data to most effectively support decision-making efforts of policymakers and practitioners allocating aid remains unanswered. This experiment will help to fill this gap through a comparison of aid allocation decisions using three different presentations of the same information.

Hypotheses

Hypothesis 1: Seeing data presented in the form of a map will lead to better decisions than if data is presented in the form of a spreadsheet or dense document.

The purpose of providing a map of aid and poverty information is so that individuals can see large amounts of complex data displayed visually in an easily understandable format. We believe that the map condition will lead to the most efficient aid allocation decisions because maps combine the multiple pieces of information needed to perform the task of determining how much aid should be given to each district. This method of information presentation should be the most useful tool in the completion of this complex cognitive task.

Hypothesis 2: The inclusion of biased stories with correct factual information will result in inefficient aid allocation decisions.

The inclusion of biased stories of children in certain districts should lead to higher than optimal allocations of aid to those districts. Participants' exposure to these stories should make them more likely to allocate more aid to districts with accompanying stories because participants will be able to identify with the humans in the stories to some extent, as the stories will be more salient than the strictly factual data presented with numbers.

Research Design

Outcome Measure

Participants were given access to an online form through Qualtrics and asked to complete the following task: *You are a policymaker in Malawi in the year 2011 and you must decide how to allocate $33 million from a World Bank project to the 26 districts in your country. Use the information given to you to decide how much money each district should receive. There is no minimum or maximum dollar amount that each district must receive, but the total across all districts must equal $33 million. The optimal allocation will take into account the number of people in poverty in each district (reach as many* *poor people as possible) and the amount of aid given to each district in the last five years (historically underserved areas should get more money).* Participants were then evaluated based on how close they were to achieving the "optimal" allocation of aid across the 26 districts with respect to the information provided. In addition to evaluating the effectiveness of each participant's aid allocation decisions, we evaluated the time required to make the aid allocation. We are also able to compare the allocations of participants in different treatment groups to see if allocation patterns differ systematically across treatments.

Treatment and Control Conditions

Participants were randomly assigned to six treatment groups, as shown in the table below:

	No Story	**Story**
Detailed document	1	2
Spreadsheet + Detailed document	3	4
Map + Detailed document	5	6

We followed a full factorial design, with treatments based on a combination of two factors: delivery of information (large document, spreadsheet and large document, or map and large document), and inclusion or exclusion in the detailed document of personal stories about individuals living in districts. More information about each of these treatment documents is given below.

Detailed document (and stories): This document included basic information about each district in Malawi, including population, poverty rates, and amount of past aid given to the district. There were be two versions of this detailed document: one with personal stories randomly assigned to be included with the information for number of districts, and one without the personal stories. Each participant received one of the two versions of the detailed document.

Spreadsheet: Participants in the spreadsheet treatment groups saw a spreadsheet that included the following information for each district: number of people in poverty in 2011 and the total amount of aid that each district has received from 2007-2011. The spreadsheet was a static document that subjects could not download.

Map: Participants in the map treatment groups saw a map that included the following information for each district: number of people in poverty in 2011 and the total amount of aid that each district had received from 2007-2011.

Subject Pool

Participants in the Mapping Experiment were drawn from a pool of students at the College of William and Mary through the Government department. It was anticipated that 180 students would participate in the experiment, ranging in age from 18 to 24. 223 students actually participated in the experiment. We expected that about half of the participants will be male and half will be female.

We worked with the Government department at the College of William & Mary to recruit students through the Omnibus project, through which students received extra credit for their participation in the experiment. There were no unique characteristics required for participation in the study.

Randomization Procedure

Each participant was randomly assigned to one of our six treatment groups. The Qualtrics platform was set up such that each student would randomly complete the experiment by being shown one of the six treatments at random. Due to the nature of the subject pool through which our subjects were recruited, we did not have access to any information about our study participants before their participation in the experiment occurred.

Challenges and Limitations

The main limitation to this study is that our subject pool does not have the same knowledge and experience pertaining to international development that our target group of interest has. We plan to address this problem with external validity in the future as we eventually hope to perform this study with development professionals. A large challenge with this study is providing our subjects with a realistic task to complete. There are no conditions under which the information and directions we give our subjects will perfectly mirror real-world situations, so our attempts at assigning a task and providing background information will be imperfect, especially during this first attempt at a pilot test of this study. The limits to external validity of this study will be an important consideration throughout this pilot process.

Discussion of Results

Before analyzing the data from our experiment, we were faced with a decision of how to handle observations that were inconsistent with our target outcome measure due to human error on the part of the subjects. Rather than eliminating all respondents who did not total aid amount across the 26 districts to $33 million (using an acceptable range of $32.99-33.01 million), we normalized allocations across individuals such that the proportions of total aid allocated to each district by each individual remained the same, but all allocations totaled $33 million. In order to account for these human error discrepancies, we created a binary variable to indicate whether the original allocation amount actually totaled $33 million. Second, we created another binary variable to indicate whether study participants did not fully engage in the task. There was wide variation in the time spent on the given task; this has been reflected in a variable indicating whether study participants spent three minutes or less on the aid allocation task. Approximately one quarter of respondents fell into this category of spending only three minutes or less on the task.

Before beginning analysis, we performed randomization balance checks to ensure that our treatment groups were balanced across a few covariates: including gender, class year, and self-reported international relations knowledge.

Covariate Means and Balance

		Means			*Differences*	
	Map	Spreadsheet	Document	Sheet - Map	Doc – Map	Doc – Sheet
Gender	0.49	0.58	0.48	0.09	-0.01	-0.10
				(0.08)	(0.08)	(0.08)
Class Year	2.72	2.41	2.51	**-0.31****	**-0.21***	0.10
				(0.14)	**(0.16)**	(0.15)
IR Knowledge	2.93	3.19	3.18	0.26	0.25	-0.01
				(0.21)	(0.22)	(0.24)
N	80	73	67			

One-tailed statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

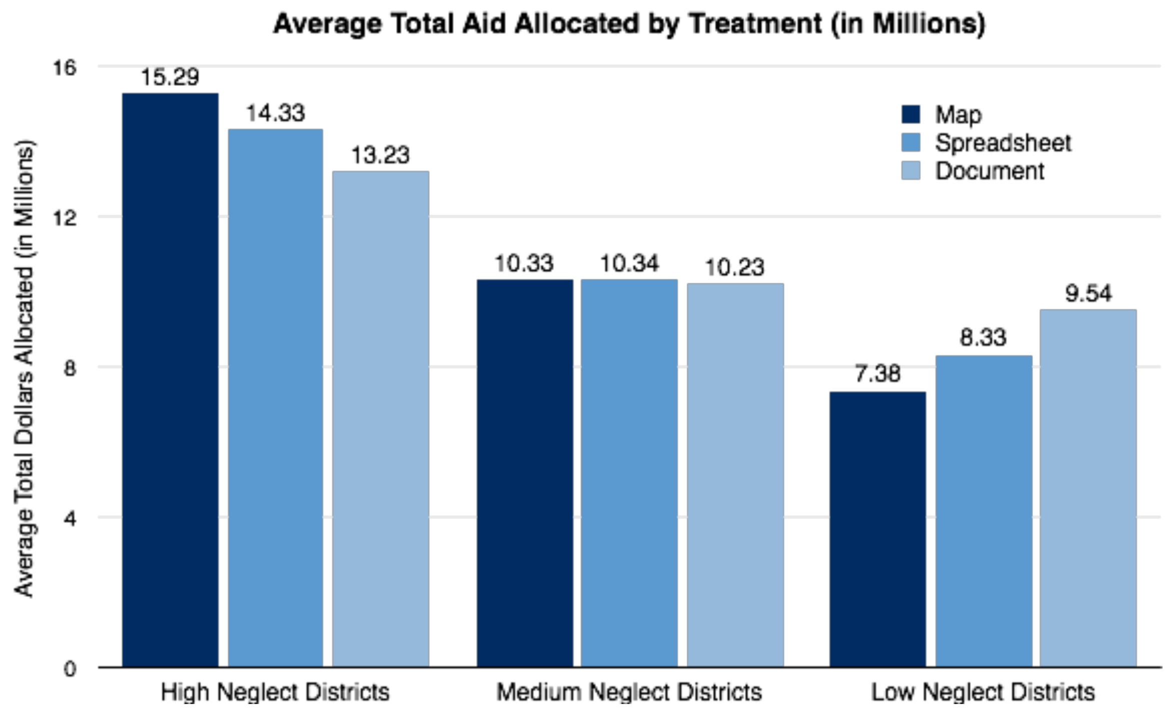
There were no statistically significant differences across treatment groups for gender or international relations knowledge. The one area where statistically significant differences emerged across treatment groups was class year. We believe that this should not have a significant effect on our analysis, however, as the difference between a college sophomore and a college junior will likely not have a strong impact on allocation decisions.

In order to more fully understand the treatment effects found in our experiment, we analyzed our data in several ways. We first compared aid allocation decisions of our treatment groups against other treatment groups. To simplify these analyses, we broke the 26 districts down into groups. The purpose of comparing the allocation decisions of our treatment groups in relation to these aggregate categories was to see if systematically different decisions are made in different broad groups of districts. We created district groups to specifically reflect the task that we asked participants to complete: low neglect, medium neglect, and high neglect. In this case, neglect is defined as amount of previous aid for each poor person in each district. Because respondents were asked to allocate the hypothetical aid money to districts based on a combination of both previous and absolute number of people in poverty, we believe this set of comparisons provides the best standard against which to judge the effectiveness of allocation decisions.

Comparisons of Treatment Groups

In order to easily compare allocation decisions made by each treatment group, we grouped the districts of Malawi by levels of poverty and levels of previous aid received by each district, then performed difference in means tests for our treatment groups in an attempt to uncover systematic differences across treatments to these groups.

High, Medium, and Low Neglect District Comparisons



		Means			*Differences*	
	Map	Spreadsheet	Document	Sheet - Map	Doc – Map	Doc – Sheet
High Neglect	15.29	14.33	13.23	-0.95 (.88)	**-2.06**** **(.90)**	**-1.11*** **(.84)**
Medium Neglect	10.33	10.34	10.23	0.00 (.71)	-0.10 (.82)	-0.11 (.77)
Low Neglect	7.38	8.33	9.54	**0.95*** **(.63)**	**2.16***** **(.79)**	**1.21*** **(.78)**
N	81	74	67			

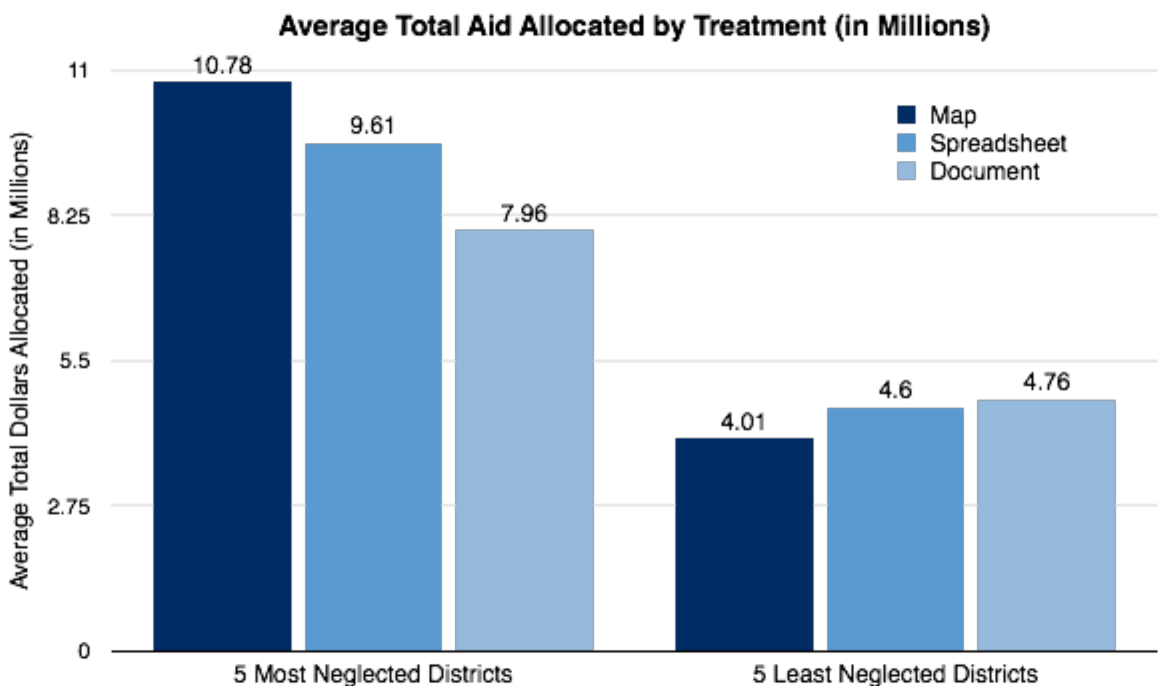
One-tailed statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

We first examined differences in allocation decisions across treatment groups with respect to three categories of districts in Malawi based on neglect (defined here as previous aid dollars per poor person in each district). While allocation decisions differed only very slightly in the "Medium Neglect" districts, the differences in allocation decisions for "High Neglect" and "Low Neglect" districts were quite large.

When making allocations to high neglect areas, study participants who were given a map rather than just a PDF document on average allocated a total of $2.06 million more to this collection of districts most in need ($15.29 million in the map condition, compared to $13.23 million in the document condition). This difference, as well as the difference in allocations by the spreadsheet group and the document group, was statistically significant.

In low neglect districts, all treatments led to statistically significant differences in allocation decisions. For example, participants who were given a map allocated on average $2.16 million less to this collection of districts than did participants using only a PDF document.

5 Most Neglected Districts and 5 Least Neglected Districts Comparisons



	Means			*Differences*		
	Map	Spreadsheet	Document	Sheet - Map	Doc – Map	Doc – Sheet
5 Most Neglected	10.78	9.61	7.96	-1.17 (.91)	**-2.82***** **(.91)**	**-1.65**** **(.87)**
5 Least Neglected	4.01	4.60	4.76	**0.59*** **(.43)**	**0.75**** **(.44)**	0.16 (.48)
N	81	74	67			

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

We next examined allocation decisions for just the five most and five least neglected districts. The results show that participants using a map to support their aid allocation decisions completed the given aid allocation task most effectively, allocating more aid to those most in need. In the five most neglected districts (those receiving the fewest previous aid dollars per poor person), individuals given a map allocated on average a total of $10.78 million, compared to $9.61 million from those given the spreadsheet and $7.96 million from those given only the lengthy document. The mean differences in total allocations between those receiving a map versus a document and those receiving a spreadsheet versus a document were highly statistically significant.

In the case of the five least neglected districts (those receiving the most previous aid dollars per poor person), participants using a map also outperformed the others. Because these districts had already received more assistance for their impoverished citizens, they should have received fewer aid dollars. Participants using a map allocated on average the least total funding to these districts ($4.01 million), compared to $4.60 million from those using a spreadsheet and $4.76 million from those using only the PDF document. The mean differences between those using a map versus a document and between those using a map versus a spreadsheet again were statistically significant.

We also performed difference-in-means tests to examine whether treatments had any impact on a few other outcomes that we observed. These outcomes were (1) minutes spent on the aid allocation task; (2) whether the participants spent less than three minutes on the aid allocation task; and (3) whether participants did not actually allocate a total of $33 million across all 26 districts prior to our normalization of the allocation amounts.

	Means			*Differences*		
	Map	Spreadsheet	Document	Sheet - Map	Doc – Map	Doc – Sheet
Minutes on Task	36.39	17.07	38.51	-19.32	2.12	21.44
				(19.79)	(28.17)	(22.35)
Below 3 Minutes	0.19	0.21	0.28	0.02	**0.10***	0.08
				(0.06)	**(0.07)**	(0.07)
Allocation Not $33m	0.12	0.15	0.10	0.03	-0.02	-0.04
				(0.06)	(0.05)	(0.06)
N	80	73	67			

One-tailed statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

These difference-in-means tests give interesting insight on impacts of our map, spreadsheet, and PDF document treatments. First, those who were given a spreadsheet to make their allocation decisions spent much less time on the allocation task. This difference, although not statistically significant, is rather substantive given that subjects in the spreadsheet treatment group spent an average of about 20 minutes less on the allocation task than did participants in other treatment groups. A statistically significant time difference does emerge when looking at the subset of participants who spent less than three minutes on the allocation task. The difference in average numbers of respondents who spent less than three minutes on the task is statistically significant between the document group (more participants spending less than three minutes) and the map group (fewer participants spending less than three minutes). This suggests that, on average, those in the map treatment group spent more time carefully analyzing the spatial allocation task at hand while those in the document group chose to quickly complete the task rather than to spend time carefully gathering all necessary information before making their decisions.

	Basic Models			*Including Controls*		
	(1) High Neglect	(2) Medium Neglect	(3) Low Neglect	(4) High Neglect	(5) Medium Neglect	(6) Low Neglect
Map Condition	**2.06** (0.89)**	0.10 (0.82)	**-2.16*** (0.81)***	**1.65* (0.96)**	-0.18 (0.95)	**-1.47* (0.78)**
Spreadsheet Condition	1.11 (0.84)	0.11 (0.78)	-1.21 (0.80)	1.44 (0.94)	-0.43 (0.91)	-1.01 (0.82)
Gender				0.36 (0.79)	-1.01 (0.70)	0.65 (0.61)
Class Year				0.14 (0.46)	-0.35 (0.47)	0.20 (0.39)
IR Knowledge				-0.22 (0.29)	0.17 (0.31)	0.05 (0.23)
Constant	**13.23*** (0.60)***	**10.23*** (0.63)***	**9.54*** (0.67)***	**13.29*** (2.10)***	**12.47*** (1.87)***	**7.24*** (1.95)***
N	222	222	222	187	187	187
Prob > F	0.07	0.99	0.03	0.43	0.77	0.21

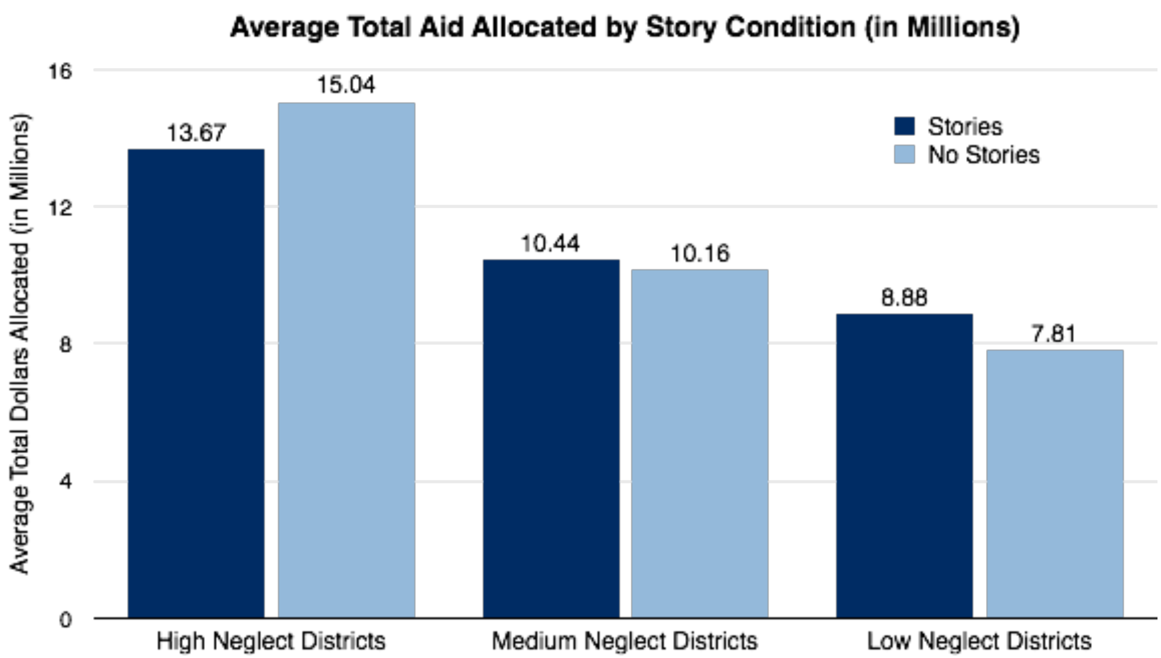
R-squared	0.02	0.00	0.04	0.02	0.02	0.03

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

	Basic Models		*Including Controls*	
	(7) 5 Most Neglected	(8) 5 Least Neglected	(9) 5 Most Neglected	(10) 5 Least Neglected
Map Condition	**2.82*** (0.90)**	**-0.75* (0.44)**	**2.49** (1.03)**	-0.40 (0.46)
Spreadsheet Condition	**1.65* (0.86)**	-0.16 (0.48)	**1.74* (1.02)**	-0.26 (0.44)
Gender			-0.13 (0.85)	0.44 (0.35)
Class Year			-0.15 (0.46)	0.19 (0.21)
IR Knowledge			-0.12 (0.29)	-0.04 (0.14)
Constant			**9.20*** (2.25)**	**3.43*** (0.91)**
N	222	222	187	187
Prob > F	0.01	0.19	0.15	0.60
R-squared	0.04	0.01	0.03	0.02

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

Story Condition Comparison



	Means		*Difference*
	Stories	No Stories	No Stories - Stories
High Neglect	13.67	15.04	**1.36****

			(.72)
Medium Neglect	10.44	10.16	-0.29
			(.62)
Low Neglect	8.88	7.81	**-1.07****
			(.60)
N	112	110	

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

	Means		*Difference*
	Stories	No Stories	No Stories - Stories
5 Most Neglected	8.91	10.18	**1.27****
			(0.74)
5 Least Neglected	4.69	4.18	**-0.51***
			(0.37)
N	112	110	

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

The inclusion of biased, emotional stories alongside the factual information given in each condition led to decreased efficiency in aid allocation decisions. These results are evident in the high and low neglect districts. In high neglect districts, the areas most in need, study participants that saw biased stories in addition to their factual materials did not allocate as much money as those that did not see the stories. This result suggests that participants in the story condition were attempting to avoid the effects of the stories by allocating fewer total dollars to high-need districts. In low neglect districts, the opposite was true. This is the most striking result in the case of the story conditions, as it appears here that the presence of biased stories led to inflated allocation to the areas that were least in need of additional funding and insufficient allocation to the areas most in need of additional funding.

	Basic Models			*Including Controls*		
	(1) High Neglect	(2) Medium Neglect	(3) Low Neglect	(4) High Neglect	(5) Medium Neglect	(6) Low Neglect
Story Condition	**-1.36***	0.29	**1.07***	**-1.48***	0.46	1.03
	(0.72)	(0.62)	**(0.60)**	**(0.81)**	(0.72)	(0.63)
Gender				0.28	-0.98	0.70
				(0.78)	(0.68)	(0.61)
Class Year				0.25	-0.35	0.11
				(0.45)	(0.47)	(0.40)

IR Knowledge				-0.19 (0.29)	0.15 (0.31)	0.04 (0.24)
Constant	**15.04***** **(0.51)**	**10.16***** **(0.37)**	**7.81***** **(0.45)**	**14.91***** **(1.84)**	**12.04***** **(1.56)**	**6.04***** **(1.74)**
N	222	222	222	187	187	187
Prob > F	0.06	0.64	0.08	0.28	0.61	0.49
R-squared	0.02	0.00	0.01	0.02	0.02	0.02

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

	Basic Models		*Including Controls*	
	(7) 5 Most Neglected	(8) 5 Least Neglected	(9) 5 Most Neglected	(10) 5 Least Neglected
Story Condition	**-1.27*** **(0.74)**	0.51 (0.37)	**-1.54*** **(0.89)**	**0.77**** **(0.35)**
Gender			-0.20 (0.85)	0.48 (0.34)
Class Year			0.01 (0.47)	0.14 (0.20)
IR Knowledge			-0.11 (0.30)	-0.06 (0.13)
Constant	**10.18***** **(0.54)**	**4.18***** **(0.26)**	**11.17***** **(1.97)**	**2.93***** **(0.83)**
N	222	222	187	187
Prob > F	0.09	0.17	0.32	0.10
R-squared	0.01	0.01	0.02	0.04

One-tailed statistical significance: * p < 0.10; ** p < 0.05; *** p < 0.01

Discussion

What We've Learned

This pilot study provided several key insights for how to conduct future research on the effect of data presentation on aid allocation decisions. In future research on this topic, we recommend using a platform that does not allow subjects to use other programs while completing the experiment. In this case, we do not know what additional resources or applications individual participants made their allocation decisions. Participants could have created a spreadsheet to manage information contained in the long document, or they could have copied and pasted information from the spreadsheet condition into Excel. Additionally, participants could have used the internet to research this specific project or to look up information about districts in Malawi.

Due to the nature of this subject pool, we were not able to block randomize participants across the six conditions. Our initial plan was to block randomize by gender and class year, but because we had no information about our subjects before they participated in the experiment, this was not possible. We recommend that future research use block randomization to help balance the composition of treatment groups across all conditions and therefore reduce bias.

For this experiment, we used Qualtrics Online Survey Software. While Qualtrics has many helpful features, using Qualtrics also presented some constraints for our research. It was difficult to embed information side-by-side, which meant participants had to scroll between the information we provided and the place they recorded their aid allocations. Moving back and forth between the data and the aid allocation undoubtedly had some impact on the cognitive complexity of the task. We suspect that in the "real world," people would print materials, take notes by hand, use two screens, or find another way to look at their decision-making notes and the data in tandem. Finally, we recommend that future explorations of this topic embed a sortable 'spreadsheet-like' table in the survey software, rather than the static table we used, as this would more accurately represent likely conditions for decision makers responsible for allocating aid.

Given the time constraints of the semester schedule, we were not able to fully pre-test the survey. We gained important insights through limited pre-testing with a group of William & Mary research assistants, but would have liked to go through several rounds of pre-testing. In expansions of this project, we recommend that the research team use pre-testing to identify areas of the survey that need refinement (e.g., how much time is reasonable to allow for completion?).

Finally, future research should consider whether to limit the amount of time participants spend on the task. In our pilot, time spent on the task ranged from [INSERT RANGE IN MINUTES]. While development practitioners likely do not have to make aid allocation decisions in a sixty minute time frame, they are busy and must manage competing demands on their time. It is likely they make some aid allocation decisions under time constraints. A time constraint also ensures some continuity across participants.

Experiment Extensions

In addition to the lessons learned in conducting the experiment, there are several extensions to the research project which have the potential for revealing more information on the effect of data presentation on aid allocation decisions. In this experiment, participants made their allocation decisions using the detailed document, the detailed document plus a spreadsheet, or the detailed document plus a map. Although each of these mediums presents the information in a different visual format, an extension of this experiment could instead isolate one information presentation component. For instance, the experiment could be limited to the visual representation of aid projects in the the map. Much of the previously cited literature points to differences in how individuals make decisions based on the visual presentation of the data. Thus, an added extension of this experiment would be to make various kinds of maps that display the aid information in a different ways and to use these as treatments instead of the detailed document and the spreadsheet. Through isolating and extending the map treatment, lessons can be learned about the optimal way to visualize aid information specifically in a map to improve aid allocation decision making.

One of the constraints faced in carrying out this experiment revolved around the fact that study participants took the survey online instead of completing it in a lab setting. Although the online setting allows participants to take the survey when convenient in their schedules, this decreases the amount of control over the experiment. In an online environment participants can easily navigate away from the page, take a break and resume at their leisure, or search the internet for more information (as highlighted previously). This inherent lack of control may call into question the findings of the experiment. An easy way to rectify this situation in future experiments would be to perform the experiment in a lab setting where there would be much more control. The amount of time participants could spend on the experiment could be controlled in addition to ensuring that other programs are not used to assist in making aid allocation decisions.

Lastly, the experiment could be conducted without the stories that were included in the detailed document. The utility of the stories as either providing more information or biasing the aid allocation decisions of the study participants is not clear. Although initially this seemed like a good way to measure the degree to which individuals make decisions based off of biased information rather than fact, this treatment may not have been strong enough to completely capture this phenomenon.

Conclusion

[[add in after we have results]]

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