Optimizing Impact for the Mobile Era – Final Report

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9/30/2013

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Mobile phone use in developing countries is booming. The worldwide number of mobile subscribers now sits at 6 billion and counting (as of 2012), with a staggering 5 billion mobile phone users in developing countries (World Bank 2012). In step with the rise of mobile phone penetration in the developing world, a wave of research has been dedicated to studying new ways to use mobile phones as a tool for growth. This includes, among many others, reducing information asymmetry (Abraham 2006), reminders for health (Lester et. al 2010; Pop-Eleches et. al 2011; Zurovac et. al 2011), savings (Karland et al. 2010), advice (Cole and Fernando 2012; Aker 2011), risk sharing (Jack and Suri 2011), and charity (Blumenstock et. al 2011).

The spread of mobile phones have reduced transaction costs between end-users, end-users and services and researchers and end-users. Regarding the latter, the penetration of both access and facility with mobile phones allow researchers a new paradigm in communicating and learning from individuals around the world. In order to take advantage of this newly available medium, it is important to understand both the benefits and limitations of mobile surveys in comparison to traditional in-person surveys. Health researchers have studied the methodological differences between phone and in-person survey administration and found relatively stable results (Weeks et. al 1983; Aneshensel et. al 1982). However, little is known if the accuracy, and efficiency that make mobile interviews so promising holds when taken to a developing country context.

This study aims to quantify and provide insight into utilizing mobile phone technologies to potentially create cost-effective, high-quality and *high frequency* data. We study this in the form of a randomized controlled trial in western Kenya. *We find that, when used in the right situation, optimizing surveys for mobile administration can be accurate, cost effective and allow for data collection that would simply be impossible any other way*. The remainder of this paper is as follows: Section 2 discusses the background and the experimental methodology, section 3 discusses the response rates of mobile surveys compared to in-person surveys, section 4 analyzes the accuracy of mobile interviews, section 5 compares costs between survey administration types, section 6 provides insight into advantages of mobile surveys and section 7 concludes.

Section 2: Background and Experimental Methodology

Our study took place between March and August, 2103 in Rarieda, a peninsula off of Lake Victoria in Western Kenya. Our sample was drawn from an existing impact evaluation of *Give Directly, Inc.*, an international NGO who makes unconditional cash transfers to poor households in Kenya. Our study randomly sampled (stratified by gender and *Give Directly* treatment status) 150 respondents from the existing study and thus, should be able to provide with unbiased estimates from which to compare survey methodologies. An advantage to drawing a sample from this study is that we are able to utilize previously administered in-person surveys to serve as a point of comparison for the accuracy of our mobile surveys. Each respondent was given a mobile phone and SIM card (Safaricom) and asked to participate in the following surveys:

1) High Frequency Calls – Daily phone calls over 10 weekdays
2) Low Frequency Call – Single phone call over 2 week period
3) High Frequency SMS – Daily SMS survey over 10 weekdays
4) Low Frequency SMS – Single SMS survey over 2 week period

Respondents were randomly placed into one of six groups that varied with respect to survey order, and time. In addition, we randomly allocated each of the 150 respondents into a 'Prize' condition – each respondent was assigned to receive either a *high* (100 Ksh) or *low* (50 Ksh) base incentive for each survey completed. Crucially, all respondents were recruited under the guise of receiving a *low* prize, a subset of which was subsequently "surprised" with a higher incentive. This allows us to isolate the effect of the incentive on response rates without concern for prizes influencing selection into the study.[3]

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[3] This technique was popularized by Karlan and Zinman (2009)

All mobile surveys were conducted in Nairobi, Kenya at the Busara Center for Behavioral Economics. Trained enumerators carried out the phone surveys, while the SMS survey was done automatically using *Telerivet* (http://telerivet.com).

Section 3: Response Rates

An important component in administering mobile surveys is simply getting the individual on the other end of the line to pick up their phone. Blumenstock finds in Rwanda that 38% (588/1,529) never answer in response to a phone survey and of those who do pick-up 2% refuse despite $1 completion incentive (Blumenstock 2012). Our choice of sample also allows us to directly compare the attrition of mobile surveys to in-person surveys as the respondents in our study had previously been surveyed up to three times.

In-Person Attrition

The previously conducted study from which we drew our sample population carried out two waves of in-person interviews – a baseline survey between May and November 2011 and an endline survey between September and December 2012. They find a response rate of 929/990 (92.9%) between the two surveys.

Mobile Attrition

Table 1 provides summary statistics and response rates for the 4 different mobile survey types. Responses to phone calls were much higher than to SMS. Low-frequency phone calls were comparable to in-person response rates (95% vs. 92.9%), while even high-frequency calls maintained a strong response rate (82%). The average respondent participated in about 15 surveys over the course of the study and only a single individual completely failed to participate in any survey.

Determinants of Response

Next we turn to determinants of response. We run a parsimonious OLS regression where our dependent variables are the number of completed surveys of each type and in total. Our explanatory variables include indicators for incentive type, *Give Directly (GD)* treatment status, gender and group. We see very little overall effects on response rates; interestingly neither the incentive level nor *GD* treatment status is significant in any specification. It seems then that incentives don't matter (unlikely) or that our choices of incentives were not enough to trigger demand effects. The fact that the *GD* coefficient is insignificant quells some concerns about experimenter demand effects and selection bias. Intuitively, one could imagine that being a previous recipient of *Give Directly* instills a stronger sense of relationship between the researcher and respondent. However, this is not necessarily the case. For one, our study (and the study before it) was conducted through a third party *Innovations for Poverty Action*. In addition, because participants in our study received a free mobile phone and the opportunity to earn money, intrinsic motivations can be crowded out by monetary concerns. [4]

Overall, we find relatively high response rates to mobile surveys. These findings deserve two final caveats. On one hand, the respondents in our sample are rural; with less experience using phones and in areas with poorer cellular reception and low access to electricity. This would tend to understate the response rates. However, on the other hand, previous research, personal introductory visits and sizeable incentives drive response rates to what should probably be considered an upper bound.

Section 4: Accuracy of Mobile Surveys Compared in In-Person Surveys

"Distributional Stability"

To paint a better picture of the cost-benefit tradeoff with mobile surveying, we analyze the accuracy of mobile surveys with respect to in-person. As previously mentioned, we

[4] In fact, one could argue that given the incentives, those who have not received money from *GD* may be more likely to respond. However, unreported regressions that explore interaction terms between incentives and treatment type do not materially change the results.

exploit the fact that all of our respondents had participated in both a baseline and endline survey between 2011 and 2012 to obtain data on in-person responses. Because we do not conduct the mobile and in-person surveys simultaneously, we cannot simply compare administration types. That is, we must account of temporal fluctuations or trends in the data. To control for these possible changes, for each variable we first run a two-sample Kolmogorov-Smirnov (K-S) test for equality of distribution functions between baseline and endline responses. Next, we run the same test, but this time between endline and mobile survey response (phone or SMS). For those variables which we cannot reject the null hypothesis in the first case, we assume them to be temporally "stable". Then, we should expect those variables to remain stable between the endline and the mobile survey. In the case that we can reject the null hypothesis in the first case, we have no prior about the distributional "stability" between the endline and mobile survey.[5]

Figures 1-3 highlight this analysis. Figure 1 plots the kernel densities of the CESD scores from the baseline and endline surveys. The p-value on the K-S test fails to reject the null hypothesis that these values are drawn from the same distribution. We then classify the CESD score as temporally "stable". Thus, we should expect to fail to reject the null hypothesis for the K-S test between the endline and phone survey, and the endline and SMS survey. Figure 2 and Table 3 show that, for endline and phone surveys, we *do* reject the null of equality of distribution. This lends evidence to the fact that CESD via phone administration leads to a different distribution of responses than when conducted in-person. Figure 3 shows that CESD via SMS has the opposite result; the K-S test fails to reject the equality of distribution.

Table 3 shows some of the variables tested. You can see that phone surveys perform well when distributional stability is predicted (in 3 of 4 cases). SMS performance is mixed.

[5] For description and notes of the variables used, see the appendix.

Quantifying the discrepancy

For those variables that *lack* "distributional stability", we run an OLS regression to quantify the extent of the discrepancy. We find that, on average, phone administration reduces reported CESD depression scores by 18%. We find no significant relationship between SMS administration and reported risk preference due to collinearity of the variables.[6]

Effect of Attrition on Error Bounds

To understand the effects of attrition on responses, we calculate Lee bounds (Lee 2009). Lee bounds calculate upper and lower bounds for a 'naïve' confidence interval. Lee bounds trim samples so that the number of observed individuals is the same in each group and compare the unconditional means of the subsamples.[7] We calculate the confidence intervals from Lee bounds and compare them to the confidence intervals from an OLS regression (Table 5). Lee bounds have heterogeneous effects on the confidence intervals; in all cases they widen the confidence interval, although in regression (4) the interval is moved more strongly in the negative direction.

Overall, the data show that mobile surveys can be an accurate alternative to in-person surveys, but that special attention must be paid to content of the question and the delivery method. Responses can show considerable variation, a fact that is further exacerbated by attrition.

Section 5: The Cost of Administration

[6] Changing the specification does not affect the results (not reported).

[7] See Tauchman, 2012, for more details. Technically Lee bounds also require 1) Random assignment of treatment and 2) Monotonicity – that is that treatment status can only affect individuals in one direction. In this example, we treat phone interviews as the "treated" group while endline surveys are the "control".

In this section we will compare the costs associated with in-person and mobile surveys. For generalizability we will assume survey administration for 100 respondents and use rough costs from Kenya to illustrate the relative costs.

For in-person surveys (2.5 hours), one should budget 1/3 of a field-officer day per interview. This translates to 500 Ksh in salary, 67 Ksh in field-lunch, 333 Ksh in transport, and 30 Ksh in airtime. Also include 50 Ksh for a respondent gift and the total marginal cost of an in-person interview comes to roughly 980 Ksh per interview. For the same length of interview time, budget 1/4 field officer day per phone interview. This translates into 375 Ksh in salary. Add variable rental costs for Field Officers for a total of 825 Ksh per interview[8]. Higher frequency calls should be shorter in length and adjusted accordingly. SMS surveys should be no more than 60 questions in length. The only variable costs associated with SMS surveys are gifts and airtime (50 Ksh per person and 1 Ksh per question, respectively). Budget 130 Ksh per survey in variable costs.

Fixed costs depend on your location. Everyone must budget for research office space. In addition, each Field Officer needs either his/her own computer or tablet for recording survey responses (40,000 Ksh). SMS surveys require a single (fixed) Field Officer per day, and can run thousands of interviews. See Table 6 for a summary of survey costs.

Section 6: The Benefits of High-Frequency Data

Mobile surveys have a unique advantage that in-person surveys simply cannot match: the ability to collect high-frequency data. When a respondent is just a phone call or SMS away, it becomes simple to query him/her weekly, daily or even hourly. This high-frequency data has the ability to turn the standard baseline-midline-endline impact evaluation paradigm on its head.

[8] Including 200 Ksh in airtime and 50 Ksh for a gift, but excluding transport and lunch. In Nairobi, renting a cubicle for a field officer costs approximately 800 per day or 200 per interview.

As an exploration into the power of high-frequency data, we asked respondents on our high-frequency calls to tell us the last thing they were thinking about before the call. Figure 4 deconstructs the phrases into words where the size of the word represents its relative frequency. Next we subjectively created categories based on 200 randomly selected phrases. Then phrases were put into categories via a blind simultaneous categorization with two different Field Officers. Unmatched phrases underwent a second blind simultaneous categorization by different Field Officers, with unmatched phrases discarded.[9]

Figures 5-8 provide us a fresh insight into the minds of the poor. Figure 5 is a cumulative categorization of all participants by survey number. Figure 6 and Figure 7 disaggregates into participants of our study who had received cash transfers from *Give Directly* and those who did not. One can quickly identify the distributional differences across the two types of people. Finally, Figure 8 separates the calls into dates, allowing us to examine how thoughts change on aggregate over a 2-month time frame.

Broadly speaking, food is constantly on the top of the mind of respondents. Food is subcategorized into “Food Prep” and “Food Search”. The “Food Search” category is heavily restricted to mentions of “worry”, “how (he/she will provide food)” and “find”. This represents pressing food security issues. “Heath” is better described by ‘illness’, it represents thoughts of personal or external illness; disease, hospital visits, etc. We refrain from over analyzing qualitative data, but these figures serve as a small glimpse into what can be achieved through high-frequency data collection.

Section 7: Discussion and Conclusion

In this study we aimed to investigate how mobile devices can be used to create data that are cost-effective, accurate and innovative. We find that mobile surveys have relatively high response rates compared with their traditional in-person counterparts. We also

[9] We also discarded the categories of “Other”, “Nothing”, and “IPA”. IPA refers to thoughts by respondents of their upcoming survey, payments from surveys or issues with their phones relating to the survey.

find that although response rates are insensitive to doubling incentives, one must pay careful attention to the type of question, type of mobile survey and attrition when designing surveys that include mobile administration. Finally, we show that mobile surveys can be administered at a fraction of the cost, and be deployed with *high frequency*. High frequency data, whether it is transactional, objective, or emotional holds promise for researchers who can take advantage of the 'big data' that is collected. We have seen that even unstructured qualitative data can inspire ideas or inform analysis.

Of course mobile surveys are not a substitute for properly executed in-person surveys. Mixed methods that properly utilize the strengths and weaknesses of each type should be strongly considered. What works best for each? To this question the authors submit a few simple rules of thumb. In-person interviews work best when i) Long-form interviews are taking place with things that can not be measured over the phone (objective indicators or poverty, biomarkers, etc.) ii) Transport costs are cheap compared to office space, and airtime is expensive relative to Field Officer salary. Phone administration should be done when i) Short, frequent interviews are required, ii) Transport or labor are relatively expensive compared to airtime (respondents are geographically disbursed). Finally, SMS surveys play to their strengths when i) Sample size is large and frequency is high, ii) Questions can be answered with a simple categorical response, iii) Respondents are literate and mobile savvy.

Soon there will be a day where there are more mobile phone lines than humans. As new methods of communication serve to connect us, we must look to new methods to harness the power of communication. By studying the strengths and weaknesses of mobile surveys we hope to introduce new ideas and work towards a new paradigm by understanding, developing and deploying projects in the developing world.

References:

Abraham, R. (2006, May). Mobile phones and economic development: Evidence from the fishing industry in India. In *Information and Communication Technologies and Development, 2006. ICTD'06. International Conference on*(pp. 48-56). IEEE.

Aker, J. C. (2011). Dial “A” for agriculture: a review of information and communication technologies for agricultural extension in developing countries.*Agricultural Economics*, *42*(6), 631-647.

Aneshensel, C. S., Frerichs, R. R., Clark, V. A., & Yokopenic, P. A. (1982). Telephone versus in-person surveys of community health status. *American Journal of Public Health*, *72*(9), 1017-1021.

Blumenstock, J. E. (2012). *Essays on the Economic Impacts of Mobile Phones in Sub-Saharan Africa* (Doctoral dissertation, University of California).

Blumenstock, J., Eagle, N., & Fafchamps, M. (2011). Charity and Reciprocity in Mobile Phone-Based Giving: Evidence from Rwanda.

Cole, S., & Fernando, A. (2012). The Value of Advice: Evidence from Mobile Phone-Based Agricultural Extension. *Harvard Business School Finance Working Paper*, (13-047).

Jack, W., & Suri, T. (2011). Risk sharing and transaction costs: Evidence from Kenya’s mobile money revolution’. *Working paper*.

Karlan, D., & Zinman, J. (2009). Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. *Econometrica*, *77*(6), 1993-2008.

Karlan, D., McConnell, M., Mullainathan, S., & Zinman, J. (2010). *Getting to the top of mind: How reminders increase saving* (No. w16205). National Bureau of Economic Research.

Lee, D. S. (2009). Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *The Review of Economic Studies*, *76*(3), 1071-1102.

Lester, R. T., Ritvo, P., Mills, E. J., Kariri, A., Karanja, S., Chung, M. H., ... & Plummer, F. A. (2010). Effects of a mobile phone short message service on antiretroviral treatment adherence in Kenya (WelTel Kenya1): a randomised trial. *The Lancet*, *376*(9755), 1838-1845.

Pop-Eleches, C., Thirumurthy, H., Habyarimana, J., Graff Zivin, J., Goldstein, M., de Walque, D., ... & Bangsberg, D. (2011). Mobile Phone Technologies Improve Adherence to Antiretroviral Treatment in Resource-Limited Settings: A Randomized Controlled Trial of Text Message Reminders. *Aids*, *25*, 825-834.

Radloff, L. S. (1977). The CES-D scale a self-report depression scale for research in the general population. *Applied psychological measurement*, *1*(3), 385-401.

Tauchmann, H. (2012). LEEBOUNDS: Stata module for estimating Lee (2009) treatment effect bounds. *Statistical Software Components*.

Weeks, M. F., Kulka, R. A., Lessler, J. T., & Whitmore, R. W. (1983). Personal versus telephone surveys for collecting household health data at the local level. *American Journal of Public Health*, *73*(12), 1389-1394.
World Bank. 2012. Information and Communications for Development

World Bank. 2012. Information and Communications for Development 2012: Maximizing Mobile. Washington, DC: World Bank. DOI: 10.1596/978-0-8213-8991-1; website: http://www.worldbank.org/ict/IC4D2012. License: Creative Commons Attribution CC BY 3.0

Zurovac, D., Sudoi, R. K., Akhwale, W. S., Ndiritu, M., Hamer, D. H., Rowe, A. K., & Snow, R. W. (2011). The effect of mobile phone text-message reminders on Kenyan health workers' adherence to malaria treatment guidelines: a cluster randomised trial. *The Lancet*, *378*(9793), 795-803.

Table 1: Response Rate by Survey Type

	Mean	%	SD	Min	Max
All	15.10	69%	5.88	0	22
HF Calls	8.15	82%	2.53	0	10
LF Calls	0.95	95%	.212	0	1
HF SMS	4.41	44%	4.25	0	10
LF SMS	0.59	59%	.521	0	2
Observations			150		

HF - "High-Frequency", LH- "Low-Frequency"

Table 2: Effect of Observables of Response Rate

	(1) **All**	(2) **HF Call**	(3) **LF Call**	(4) **HF SMS**	(5) **LF SMS**
Prize==1	0.129	-0.0388	-0.0120	0.171	0.00895
	(0.14)	(-0.10)	(-0.32)	(0.25)	(0.11)
GDTreatment==1	-1.345	-0.369	-0.0519	-0.786	-0.138
	(-1.39)	(-0.90)	(-1.64)	(-1.13)	(-1.61)
Sex==1	-1.091	-0.821*	-0.0159	-0.254	-0.00117
	(-1.10)	(-1.94)	(-0.42)	(-0.37)	(-0.01)
Group==2	2.945*	-0.740	0.0390	3.212***	0.434***
	(1.76)	(-1.16)	(0.57)	(2.67)	(2.88)
Group==3	1.436	0.00718	0.0794	1.190	0.160
	(0.91)	(0.01)	(1.43)	(0.98)	(1.05)
Group==4	2.704	-1.075	0.00144	3.419***	0.359**
	(1.59)	(-1.48)	(0.02)	(2.86)	(2.40)
Group==5	1.078	-1.027	0.0383	1.827	0.240
	(0.66)	(-1.47)	(0.56)	(1.50)	(1.56)
Group==6	2.033	-0.946	0.0387	2.780**	0.160
	(1.14)	(-1.40)	(0.56)	(2.26)	(1.04)
Constant	14.67***	9.426***	0.965***	3.841***	0.439***
	(10.00)	(15.89)	(17.10)	(3.54)	(3.03)
Observations	150	150	150	150	150
R-squared	0.050	0.063	0.033	0.092	0.094
Adjusted R-squared	-0.004	0.010	-0.022	0.040	0.042

OLS regression. The dependent variable is the total number of interviews completed by type. *HF* and *LF* refer to "High-Frequency" and "Low-Frequency" respectively. Both LF variables are indicators (as low frequency surveys are administered at most once). *Prize* is an indicator equal to one if the incentive is 100 Ksh and 0 if the incentive is 50 Ksh. *GDTreatment* is an indicator equal to one if the respondent had previously received money from *Give Directly*. *Sex* is an indicator equal to one for male. *Group* is an indicator for one of the 6 randomly assigned groups that varied over survey order and time. *p<.10 **p<.05 ***p<.01

Table 3: Two Sample Kolmogorov-Smirnov test for equality of distribution functions

	Baseline-Endline (Pure control excluded)			Endline-Call/SMS (Full sample)		
	D	***P-Value***	***P-Value Corrected***	***D***	***P-Value***	***P-Value Corrected***
Phone						
Perceived Risk	0.079	0.893	0.861	0.136	0.156	0.125
Member in HH	0.0583	0.987	0.981	0.1125	0.312	0.266
Age	0.1062	0.527	0.467	0.0347	1.000	1.000
Animals	0.1695	.067*	.050**	0.1732	.026**	.019**
Assets	0.1612	.093*	.071*	0.226	.001***	.001***
Consumption	0.2655	0.000***	0.000***	0.1224	0.229	0.190
CESD	0.0832	0.853	0.815	0.192	0.012**	0.009***
SMS						
CESD	0.0832	0.853	0.815	0.0837	0.879	0.843
Risk Preference	0.1371	0.27	0.221	0.2506	.013**	.008***

Two sample Kolmogorov-Smirnov test for equality of distribution functions. Based on our "distributional stability" concept, variables with non-significant p-values when comparing Baseline-Endline should *also* have p-values that indicate non-significance when comparing Endline to Call or SMS administration. Note: Because a subset of our respondent pool were only surveyed in-person at endline, we restrict them from comparison in the Baseline-Endline K-S test ("Pure control excluded"). We subsequently include them back into the "Full" sample for comparing the Endline – Call/SMS. *p<.10 **p<.05 ***p<.01

Table 4: Effect of Survey Type on Reported Variables

	(1) **CESD Score**	(2) **Risk Prop.**
Surveytype==2	-4.712***	0
	(-4.08)	(.)
Surveytype==3	0	0
	(.)	(.)
Surveytype==4	0	0
	(.)	(.)
Surveytype==5	0	-0.0534
	(.)	(-1.23)
Surveytype==6	-0.230	0
	(-0.20)	(.)
Sex==1	-1.985*	-0.0506
	(-1.70)	(-1.12)
Prize==1	-0.652	-0.00913
	(-0.59)	(-0.20)
GDTreatment==1	-0.459	0.0862*
	(-0.41)	(1.87)
Age	0.0566	-0.00171
	(1.17)	(-1.08)
Group==2	1.884	-0.0141
	(0.95)	(-0.19)
Group==3	-1.336	-0.00136
	(-0.72)	(-0.02)
Group==4	1.158	-0.00729
	(0.57)	(-0.09)
Group==5	0.304	0.0467
	(0.16)	(0.59)
Group==6	0.202	-0.000327
	(0.11)	(-0.00)
Constant	26.01***	0.339***
	(10.88)	(3.85)
Observations	384	240
R-squared	0.083	0.034
Adjusted R-squared	0.056	-0.008

OLS regression with standard errors clustered on the individual. *p<.10 **p<.05 ***p<.01

Table 5: Effect of Survey Type on Reported Variables

	(1)	(2)	(3)	(4)
	Perceived Risk	**HH Mem**	**Age**	**Animals**
Type2==1	-1.732*	0.379***	-0.750	-1.839***
	[-3.472 0.0088]	[0.166 0.593]	[-1.989 0.489]	[-3.186 -0.492]
	(-5.2013 2.2614)		**(-5.0937 2.7112)**	**(-5.4383 -1.1234)**
Sex==1	1.258	-0.404	0.375	-1.665
	[-0.941 3.456]	[-1.044 0.236]	[-3.997 4.747]	[-3.803 0.473]
Prize==1	1.132	-0.355	-3.369	-1.129
	[-1.004 3.268]	[-1.023 0.314]	[-7.730 0.992]	[-3.255 0.998]
GDTreatment==1	0.589	0.101	1.522	3.340***
	[-1.648 2.827]	[-0.557 0.758]	[-2.977 6.021]	[1.400 5.279]
Age	-0.0763*	-0.0265**		0.0680*
	[-0.159 0.0065]	[-0.0505 -0.0023]		[0.0003 0.136]
Group==2	-0.844	-1.468**	7.426*	-1.337
	[-5.011 3.323]	[-2.624 -0.311]	[-0.400 15.25]	[-5.402 2.728]
Group==3	0.128	-0.379	3.354	-1.233
	[-4.011 4.267]	[-1.707 0.948]	[-4.496 11.20]	[-5.226 2.759]
Group==4	3.155*	0.0288	6.840**	-1.636
	[-0.376 6.686]	[-1.089 1.147]	[0.925 12.75]	[-6.129 2.858]
Group==5	0.275	-0.833	-0.702	-2.460
	[-3.900 4.450]	[-1.863 0.198]	[-7.244 5.840]	[-6.470 1.549]
Group==6	1.427	-0.654	-3.731	0.386
	[-2.544 5.399]	[-1.649 0.340]	[-9.574 2.111]	[-3.786 4.558]
Constant	47.61***	6.898***	36.37***	7.545***
	[42.82 52.40]	[5.635 8.160]	[29.28 43.46]	[2.888 12.20]
Observations	276	287	287	406
R-squared	0.060	0.114	0.096	0.079
Adjusted R-squared	0.024	0.082	0.067	0.056

OLS regression with standard errors clustered on the individual. *p<.10 **p<.05 ***p<.01

Table 6: Illustrative Fixed and Variable Costs

	Fixed Costs			*Variable Costs*						
	Rent	**Staff**	**Computer**	**Staff**	**Lunch**	**Transport**	**Gift**	**Airtime**	**Office**	**Total Var**
In-Person	*Varies*		40,000 / PAX	500	67	333	50	30		980
Call	*Varies*		40,000 / PAX	375			50	200	200	825
SMS	*Varies*	1,500 / day	40,000 / PAX				50	80		130

Prices in Kenyan shillings, 85 Ksh / 1 USD (2013).

Figure 1: Kernel density estimate of CESD (Baseline vs. Endline)

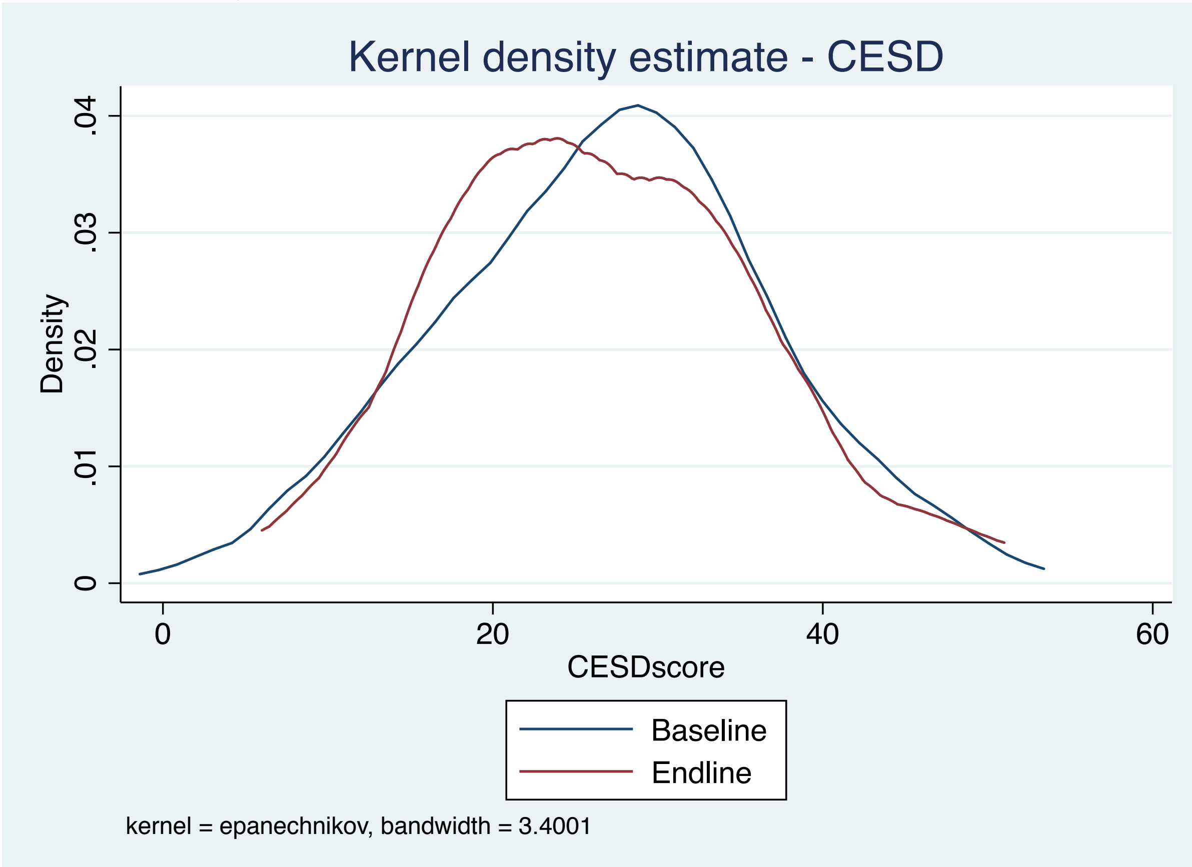


Figure 2: Kernel density estimate of CESD (Phone vs. Endline)

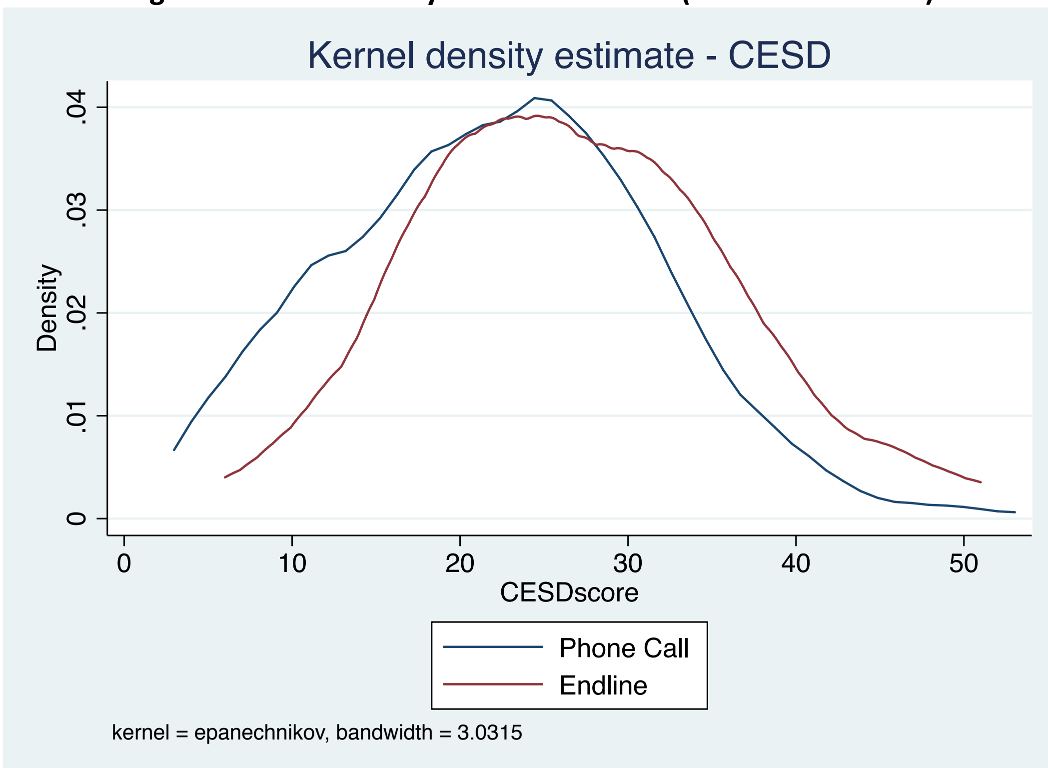


Figure 3: Kernel density estimate of CESD (SMS vs. Endline)

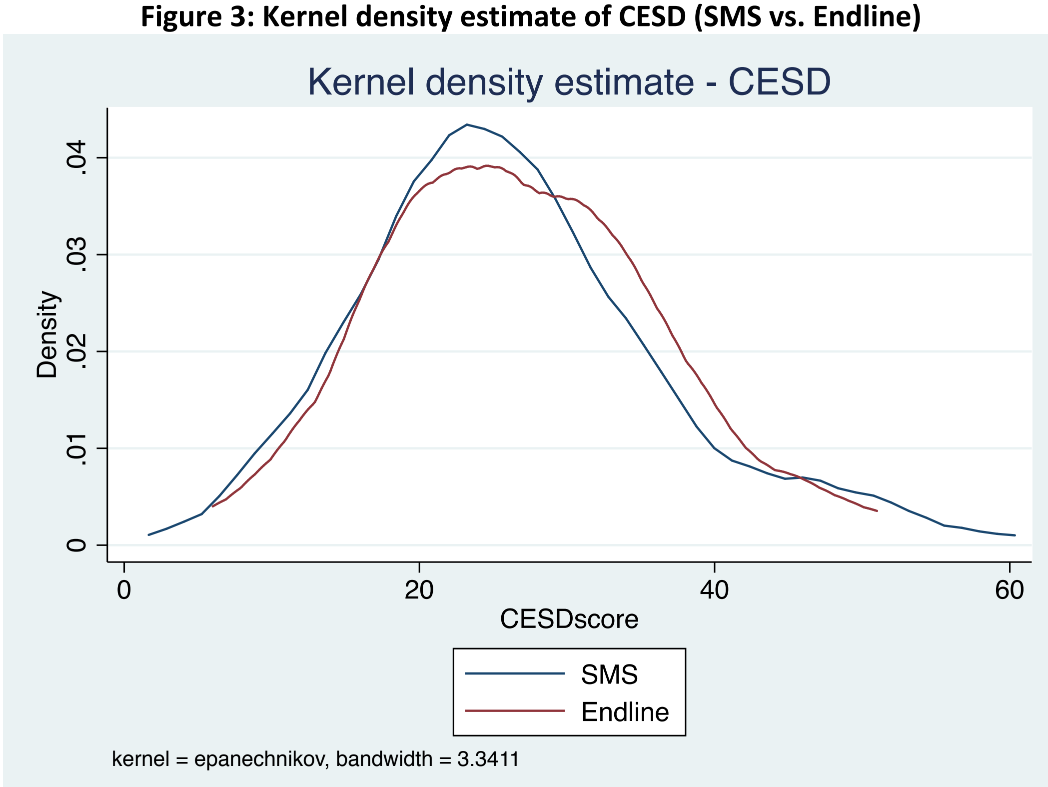


Figure 4: Responses to the question: What were you thinking right before the call?

Figure 5: Categorized Thoughts – All Subjects by Call

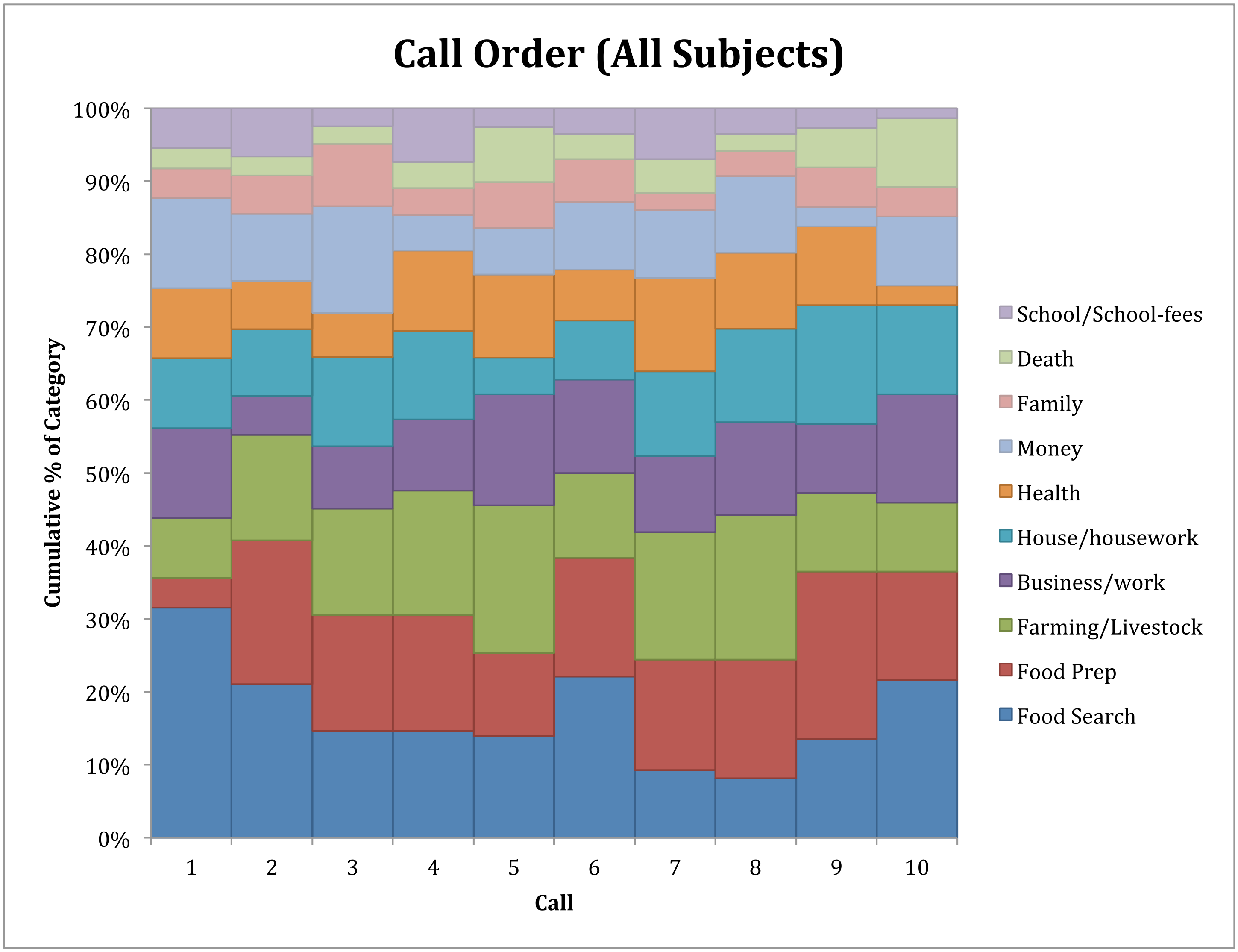


Figure 6: Categorized Thoughts – Non *GD* Recipients by Call

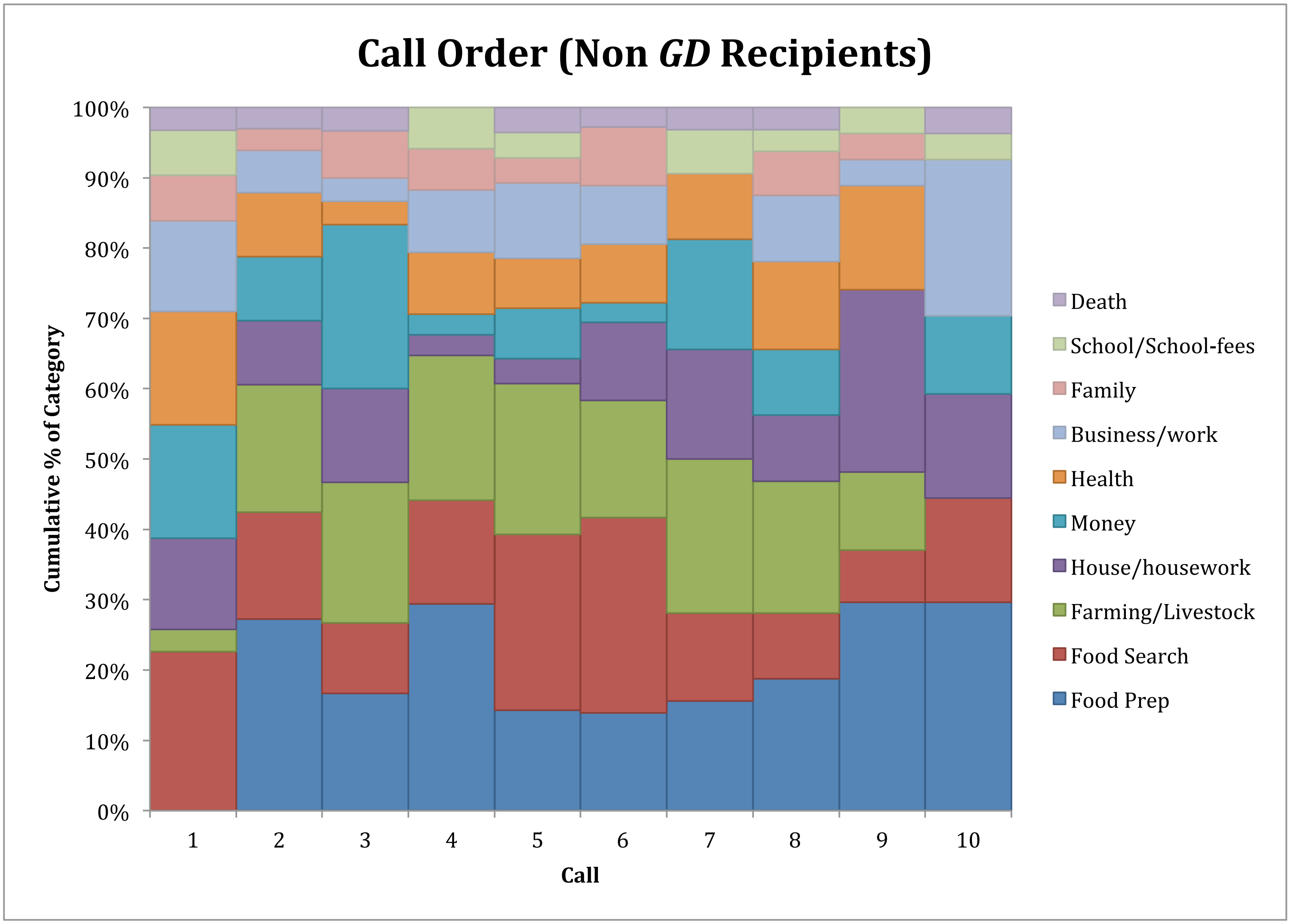


Figure 7: Categorized Thoughts – *GD* Recipients by Call

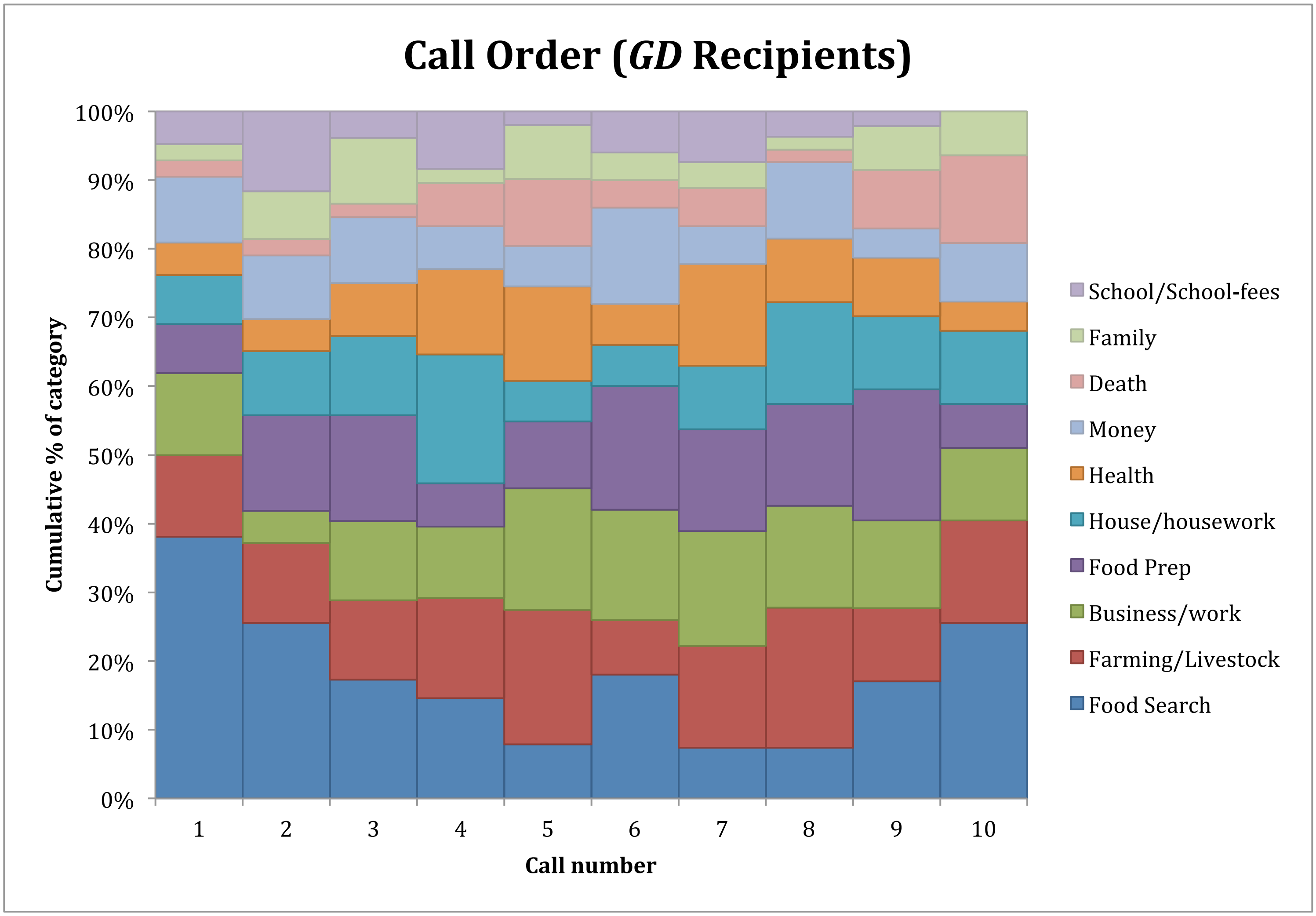
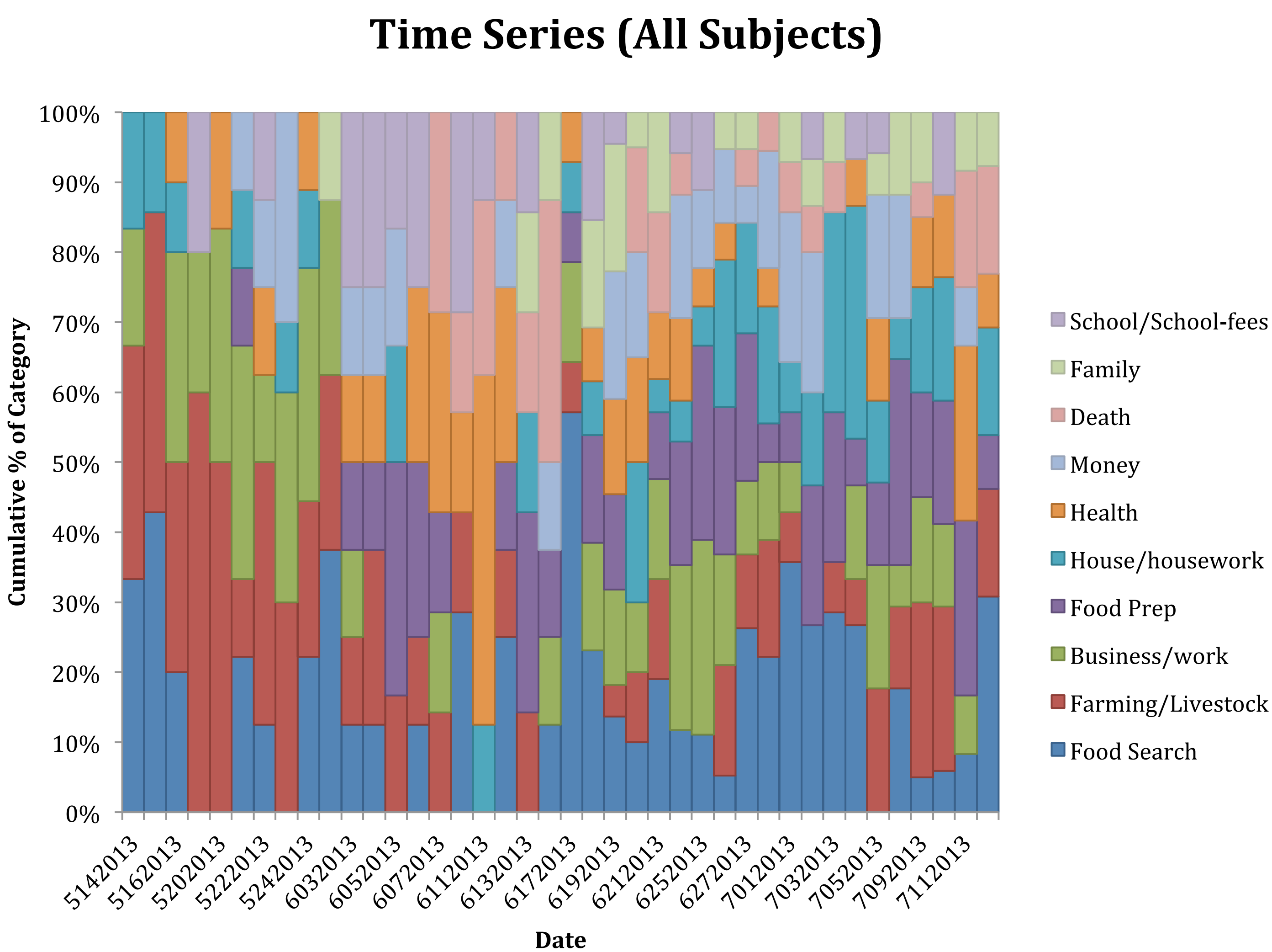


Figure 8: Categorized Thoughts – All Subjects by Date



Appendix

Description of variables

Animals: Total value (Ksh) of livestock, small livestock, and birds.

CESD: Depression scale from Radloff (1997)

Perceived Stress: Custom questionnaire, available on request.

Risk Prop: Proportion of risky hypothetical decisions. Respondents decided between 50 Ksh for sure, or flipping a coin to win 50 Ksh or 100 Ksh. Sure bets increased from 50 to 150 in steps of 10.

"What's on your mind?" Thought categories:

Business/work	non-farm work
Call	the incoming call from the FO, or IPA or GD
Death	death, funeral, funeral contributions
Family	visitors, friends, family
Farming/Livestock	tending to farm, livestock, fishing, collecting nuts
Food Prep	Preparing meals, fetching water
Food Search	Finding meals, worrying about getting enough food
Health	worrying about health, personal health, hospital visits
House/housework	managing the house, staying at home, leisure, collecting firewood
Money	tending to farm, or livestock or fishing or collecting groundnuts
School/School-fees	meetings, education, school-fees (including how to get money for fees)