THE VALUE OF COMMUNICATION FOR MENTAL HEALTH

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Abstract

Mental health disorders account for a significant share of the overall global disease burden. The economic losses from such disorders are staggeringly large, particularly in low-income countries, where people are faced with several unexpected shocks. We test whether improved communication can mitigate such mental health disorders. Partnering with a major telecommunications company, we implement low-cost communication interventions that provide mobile calling credits to a nationally representative set of low-income adults in Ghana during the COVID-19 pandemic. Individuals' inability to make unexpected calls, need to borrow SOS airtime, and to seek digital loans decreased significantly relative to a control group. As a result, the programs led to a significant decrease in mental distress (-9.8%), the likelihood of severe mental distress by -2.3 percentage points (a quarter of the mean prevalence), and domestic violence, with null impact on overall consumption expenditure. The effects are stronger for monthly mobile credits than a lump-sum. We present evidence that improvements in both business-related services and social inclusion and/or protection are relevant explanations. Simple cost-benefit analysis shows that providing communication credit to low-income adults is a cost-effective policy for improving mental health. Communication – the ability to stay connected – meaningfully improves mental well-being and interventions about communication are particularly valuable when implemented as many installments.

Keywords: *Communication* (L63, O12), *Well-being* (I38), *Mental Health and Domestic Violence* (I12, I15)

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I Introduction

Imagine that you are unable to communicate – to make a phone call, use the web, access social media, and so on – when the need arises unexpectedly. Does this matter for individuals' mental and economic well-being? Should communication interventions during pandemics be applied as a one-time large transfer or as numerous small installments? How valuable or cost-effective is a policy that provides communication credit to low-income adults for improving mental health? We use evidence from the COVID-19 pandemic to address these important questions.

Throughout the world, major communication interventions were initiated in the public and private sectors in response to the COVID-19 pandemic. In the United States, ATT Inc. provided free 10GB of internet data per month for 60 days as temporary relief for eligible customers to enable them to stay connected during lockdown, starting March 27, 2020 (ATT Inc. 2020).[1] In Ghana, the government reduced the Communication Service Tax (CST) from 9% to 5%, which reflected a reduction in the cost of mobile talk time and data purchases, effective from September 15, 2020, in response to the economic and social hardships induced by the pandemic (Ghana Revenue Authority 2020; Figure A1). The need for such communication programs was particularly crucial in developing countries where the informal sector is large and the COVID-19 crisis presented a substantial threat to individuals who face credit, savings, and psychological stressors and constraints (Banerjee, Niehaus, and Suri 2019). Despite the increase in these communication-based programs globally, there is relatively little evidence on their impacts on well-being during a pandemic.

Administrative data on mobile financial transactions from a major provider in Ghana sheds light on the potential value of communication during the pandemic. Figure A2 shows

[1]As the leading provider of mobile services in the US, with about 40% share of the market, ATT Inc.'s initiative affected a significant number of people, particularly those in the low-income communities. Others telecommunications companies, such as Comcast Corporation, have deployed similar interventions, providing essential internet and mobile services without charge to low-income families, including seniors, veterans, and people with disabilities (Comcast Corp. 2020). We provide a global review of COVID-19-induced communication programs in Tables A1 and A2.

the distribution of transactions and illustrates that while the overall market activity decreased following the onset of the pandemic, interestingly and in contrast, the demand for mobile airtime-related activities (as measured by the purchase of data and airtime amounts, and thus their demand) sharply increased over the period. This descriptive evidence documents the importance of communication during the pandemic and is congruent with our baseline surveys: 68% of individuals indicated that their need to call or connect with others (family, friends, employers) had increased due to the COVID-19 pandemic and its disruptions. Yet, between 52% and 62% indicated that, sometimes, when the unexpected need arises, they were not able to call or connect with their family and friends due to the economic hardships associated with the pandemic. Thus, programs that directly mitigate such binding communication barriers will likely have a larger impact on individual and societal well-being.

We use a randomized controlled trial (RCT) to estimate the impacts of a short-term "mobile phone calling credit" among a nationally representative set of a sub-population of low-income households in Ghana during the COVID-19 pandemic. We draw on an existing nationally representative baseline frame (Ghana Living Standards Survey 7 [GLSS7]), and focus on 1,131 low income individuals or households that are readily reachable by phone, work in the informal sector, and are located in the bottom 75th percentile of the income distribution. This sample is low income, where income and psychological constraints (Mullainathan and Shafir 2013; Ridley et al. 2020) can easily bind due to pandemic-induced economic losses, and spans 193 districts across the country's historical ten administrative regions.

We partner with a major local telecommunications company to run our experiment by randomly assigning the 1,131 individuals to two candidate communication programs: 40GHS (US$7.0) lumpsum mobile credit (376 individuals) versus 20GHS (US$3.5) monthly installments of mobile credit over two months (371 individuals) versus a control program (384 individuals); and then measuring how these affect individuals' ability to mitigate unexpected communication constraints during the pandemic, with impacts on well-being, that is, mental health, domestic violence, and consumption expenditures. The different programs about communication provide a means of examining how communication programs might be delivered: one-time large communication transfer versus numerous small installments.

The pandemic uncovered a great deal of mental health crises (World Health Organization 2022)[2] and increased domestic violence (Leslie and Wilson 2020; United Nations 2022)[3], which have potentially large short- and long-term impacts on human capital development. Mental health disorders account for 13% of the overall global disease burden (Collins et al. 2011). The economic and productivity losses from such disorders are significant, particularly in low-income countries (Mathers, Fat, and Boerma 2008; Canavan et al. 2013; Adhvaryu et al. 2019).[4] The direct economic impact of COVID-19 in these environments was high and includes earnings and consumption shortfalls (Banerjee et al. 2020), food insecurity (Laborde et al. 2020), among many other meaningful negative impacts.

How might communication affect well-being? Conceptually, communication is a network good and could turn on at least three interesting channels: (i) improved business-related services (via professional networks), (ii) improved social inclusion and/or protection (via social networks), and (iii) improved informal insurance arrangements or consumption insurance (via social networks). First, professional networks operate in form of affected individuals being able to stay in touch with customers and buy/sell with vendors to increase their revenues, which has a positive impact on mental well-being (see e.g., Ridley et al. 2020 for a detailed review). Second, social inclusion (or reduced isolation) operates in form of individuals being able to stay in touch with friends/family who can provide them emotional

[2] https://www.who.int/news/item/02-03-2022-covid-19-pandemic-triggers-25-increase-in-prevalence-of-anxiety-and-depression-worldwide

[3] https://www.unwomen.org/en/news/in-focus/in-focus-gender-equality-in-covid-19-response/violence-against-women-during-covid-19

[4] Mathers, Fat, and Boerma (2008) estimate that depression generates losses of 55.5 million disability-adjusted life-years in low and middle-income countries. Canavan et al. (2013) estimate that the productivity loss linked to mental illness is equivalent to 7% of Ghana's GDP – our country of study.

support (Mullainathan and Shafir 2013; Leslie and Wilson 2020), or serve as agents of social control and protection to specifically reduce domestic violence by increasing the cost of violence (à la Gelles 1983; Gelles and Straus 1979). Third, in vulnerable periods such as COVID-19 related lockdowns, households might have difficulty communicating with their informal insurance networks (family, friends, etc.) and thus consumption risk-sharing ability may suffer (Blumenstock, Eagle and Fafchamps 2016; Jack and Suri 2016). The provision of mobile credit might alleviate that constraint. Our interventions are designed to both relax communication constraints and test their impact on mental health, domestic violence, and consumption expenditures.

We first conduct three baseline survey waves prior to the deployment of the communication interventions. After fielding the first round of interventions (lumpsum and first installment), we conducted two endline survey waves to track the various outcomes. Our final dataset is unique due to its size and national representativeness, the expansive set of outcomes, the administrative data on mobile financial transactions, and 1×3 random variations for communication at the individual level. We find five set of results:

First, as a first stage, the interventions decreased unexpected communication constraints significantly. That is, our experimental interventions mitigate individuals' inability to meet unexpected communication needs and stay connected (-37pp=-74% for inability to make unexpected calls, -22pp=-78% for unexpected need to borrow airtime, and -3.5pp=-44% to seek digital loans). These effects are larger and more sustained over time for the installment communication credit program compared to the lumpsum credit.

Second, we find meaningful improvement in psychological well-being, which is measured using the Kessler Psychological Distress Scale (K10) and on domestic violence. Both mental distress and severe mental distress decreased by -9.8% and -2.3pp (=-24%) relative to a control group, respectively. The installment communication credit program had larger and more sustainable effects compared to the lumpsum credit. Only the installment program led to a significant decrease in the overall likelihood of individuals threatening their partners by

-6.3% (but with no impacts on the overall likelihood of individuals hitting their partners – our second measure of domestic violence).

Third, we find a null improvement in direct economic well-being. The provision of communication credits can free up an individual's resources that would otherwise have been allocated to communication for other consumption expenses. The overall effect is, however, null on total consumption, which is reassuring since the size and specificity of our intervention were not large enough to meaningfully change consumption. Only the installment communication intervention increased consumption expenditures, but the size is very small economically and only in endline wave 2.

Fourth, what explains the estimated communication impacts? We explore three alternative explanations: (i) improved business-related services, (ii) improved social inclusion, and (iii) improved informal risk-sharing or consumption insurance. We find strong empirical support for improvements in both business-related services (increased business-related income) and social inclusion/protection (reduced isolation), but not for consumption insurance. Treated individuals reported a significant increase in income (+9.0GHS per week overall) from business-related services. Similarly, treated individuals were less likely to report being emotionally- and socially-tired (-31% for the lumpsum credit group; -52% for the installment credit group) but were also more likely to stay at home during the pandemic. These show that improvements in professional networks and social inclusion are relevant explanations. We also examine heterogeneity in treatment effects along four dimensions: poverty, informality, gender, and lockdown. The effects are indistinguishable by gender but are larger for individuals that are very poor, in the informal sector, and located inside areas which were previously in lockdown.

Fifth, the marginal value of public funds (MVPF) (Hendren and Sprung-Keyser 2020) for a policy that provides communication credit to low-income adults is 2.04, suggesting that US$1.0 of spending on this communication credit policy delivers more than US$1.0 in benefits to its beneficiaries. We show robustness of the various findings to the post-double selection

LASSO estimation procedure (Belloni et al. 2014), including adjustments for multiple testing (Romano and Wolf 2005) and attrition (Lee 2009; Behaghel et al. 2015).

We contribute to three distinct literatures. First, there is almost no work connecting mental health, domestic violence and economic impacts of information and communications technology (ICT) (Jensen 2007). We offer short-run causal view of what communication does to mental health and domestic violence, connecting ICT, domestic violence and mental health. Allcott, Gentzkow, and Song (2022) examines how habit formation and self-control problems explain the usage of social media, which is different from the mental health and/or domestic violence that we evaluate. More recently, Gawai (2023) documents that broadband rollout reduces depression symptoms among older adults.[5] The theory of social control developed in sociology and applied to intimate partner violence (see e.g., Gelles 1983; Gelles and Straus 1979) predicts that societal controls and protection can increase the perpetrator' costs of domestic violence and reduce its incidence. We implement a test that provides an empirical support for the theory to explain our communication credit impacts.

Second is the economics literature on interpersonal transfers following unexpected shocks in low-income countries. Previous work have examined how households endogenously respond to non-covariate shocks by sharing consumption-related resources (Townsend 1994; Blumenstock, Eagle and Fafchamps 2016; Pulver 2009; Jack and Suri 2016). We look at a fully-covariate and prolonged shock and randomized communication transfers.

Third, we add to the growing research on mental health and economic impacts of disease epidemics (Adhvaryu et al. 2019; Banerjee et al. 2020; Archibong and Annan 2020). We cleanly isolate ICT and document how to rely on it to mitigate the mental health impacts of pandemics and unexpected hardships. Related literatures on psychiatry and epidemiology emphasize how digital technology has the potential to improve traditional psychiatry care and epidemiological outcomes. Torous et al. (2021) provide a detailed review of this emerging

[5] Related, DiNardi et al. (2019) show that an increase in broadband coverage increases the body weight (not mental health or domestic voilence) among white women, while Donati et al. (2022) documents the adverse mental health effect of broadband among the youth.

field of “digital psychiatry”.

Our results have implications for policy. Mitigation of unexpected pandemics can be a daunting task. Policymakers battle on various fronts: tackling the spread of the pandemic while easing the potential welfare impacts of the negative income shock and constraints on individuals. Our programs relax binding communication constraints (individuals inability to meet unexpected communication needs and to stay connected) and allow us to provide the first experimental evidence on the impact of communication interventions from a nationally representative set of low-income individuals on overall well-being and gender relations during pandemics. The provision of phone credit is a cost-effective policy for improving mental health and a low-cost intervention to encourage people to remain indoors during lockdown, helping to reduce infection. Thus, our results add to the space of potentially resilient policy initiatives aimed at tackling pandemics (mitigating their impacts).

We proceed as follows: In Section II, we describe the research setting, experimental design and data. Section III presents our main results. In Section IV, we examine how communication affects well-being to derive our interpretation of the results and their implications for welfare. We conclude the paper with Section V.

II Experiment: Setting and Design

II.1 A Brief Global Review: Communication Interventions

Despite their prevalence, we are not aware of any review that highlights COVID19-induced communication interventions. We begin with a careful and ambitious (yet incomplete) global search of communication-related initiatives that were introduced in response to the COVID-19 pandemic. Details are shown in Tables A1 and A2. Our review shows that several communication interventions in different forms and scales (spatial and temporal) took place during the crisis. Despite their prevalence and potential importance, there is poor evidence on the impacts of such programs during the pandemic on individuals’ economic and psychological well-being.

II.2 Research Context

Our study is set in Ghana. Mobile phone connection penetration is very high: mobile cellular subscriptions were 134 per 100 people in 2019 (rising from 70 per 100 people in 2010), even among the poor (World Bank 2020). We draw on an existing nationally representative baseline frame (GLSS7) of households in Ghana, which is housed by the implementer of our surveys (Ghana Statistical Service [GSS]). We then focus on a sub-population of low-income households (i.e., individuals/households located in the bottom 75th percentile of the income distribution). These are largely married (91%) individuals (household heads), with over 22% poverty rates and have mobile phone and connection access that is readily reachable by phone. Individuals without mobile credit can still take in-coming calls.

Similar to many countries, the pandemic in Ghana had economic impacts well beyond its health impacts, due to the restrictions on mobility and interactions that it triggered. Following the arrival of the first COVID-19 case in Ghana (March 03, 2020), the President Nana Akufo-Addo announced a lockdown in the two most economically active regions (namely, the Greater Accra Metropolitan Area and the Greater Kumasi Metropolitan Area) on March 30, which was later followed by a nation-wide closing of all schools and a ban on other activities and which extended to these affected regions.

People were advised to stay at home and were only permitted to leave their homes for essential items such as food, medicine, and water, or to visit the bank and public toilets. Intercity travel for private and commercial purposes, except for essential goods and services, was suspended. In terms of intracity travel, vehicles drivers were obliged to reduce their number of passengers to observe social distancing. The borders were closed to all but returning Ghanaians and foreign nationals with Ghanaian residence permits, who were subject to a 14-day mandatory quarantine if the returnees showed symptoms of the virus. From April 20, 2020, the lockdown was removed and some of the restrictions were relaxed, yet individuals continue to battle with the persistent impacts of these restrictions and prevailing uncertainties.

Individuals in our baseline surveys, conducted in September 2020, are much aware of the pandemic and its associated restrictions on economic activities. Almost 100% of individuals indicated being aware of COVID-19 and the restrictions, and 79% trust the government and the media to provide accurate statistics (cases, deaths) of the pandemic. Meanwhile, 68% of individuals reported their need to call or connect with others (family, friends, employers) has unexpectedly increased, yet over 52-62% were sometimes unable to connect as a result of the pandemic and its hardships. This is meaningful as 77% of the respondents are self-employed, 18% are located in previously locked-down regions, and 80% are involved either fully or partially in the informal sector. Table A3 contains more detailed summaries.

II.3 Measurement of Key Outcomes

We define the various outcome measures: communication constraints-mitigation, mental health, domestic violence, and consumption expenditures: Communication constraints-(un)mitigation measures the incidence of "(un)mitigated" mobile calls and transfers – asking whether individuals were unexpectedly confronted with the need to call or connect with others (family, friends, work) but unable to do so because they *lacked* enough communication resources to remedy the costs. Under such dire and unexpected situations (as it was during the pandemic), individuals either borrow airtime (i.e., in-kind SOS credit with a service charge of 10% and fully repayable once subscribers recharge their phone accounts with an amount that is more than the outstanding SOS credit amount) or seek digital loans (i.e., short-term digital but cashable loans with an interest of 6.9% over 30 days) from telecommunications providers. Therefore, we measure communication constraints-(un)mitigation also based on the incidence of borrowing airtime or seeking digital loans due to unexpected circumstances to connect with others.[6]

[6]Unexpected communication needs are plausibly random, with higher potential for more distress compared to needs that are expected. There is room to adjust or plan for expected

Consumption expenditures are measured across food (inside and outside home), utilities, personal care, education, health, and durables (economic well-being). Mental health is measured by the incidence of mental distress (using Kessler Psychological Distress Scale (K10)) (psychological well-being). K10 values can range from 0 (minimum) to 50 (maximum), and values above 30 are classified as severe mental distress (Adhvaryu et al. 2019). Gender relations reflect domestic violence (DV) and specifically elicit from an individual whether he/she either threatened or hit his/her partner (Banerjee et al. 2020).[7] We take advantage of our short research instrument, which is limited in space, to measure additional variables: individuals' characteristics (poverty, age, gender, educational-level, occupation, etc.), awareness and beliefs about COVID-19, COVID-19 impacts and communication constraints. We adapted a recently developed shortcut – yet rigorous, inexpensive, simple and transparent – measure of poverty called the "Simple Poverty Scorecard" (Schreiner 2015; Annan JPEForthcoming). These variables are used to test for randomization balance and explore heterogeneity in treatment effects. Summary statistics of the various well-being measures are contained in Table A3 and Figures A3 and A4. See the Appendix for specific questions and possible responses to relevant select variables.

II.4 Intervention and Timetable

We evaluate the impacts of two communication programs: lumpsum mobile credit versus installments of mobile credit. Our goal was to mitigate binding communication constraints during the pandemic that render (potentially marginal) individuals unable to connect with

needs. Thus, communication is likely more valuable to individuals when faced with unexpected needs because of the less room to adjust.

[7]We pre-specified our three primary outcomes in the AEA RCT registry (AEARCTR-0006104): (i) Information and communication-sharing (value, as measured by: unmitigated calls); (ii) Expenditures on and conditional transfers; and (iii) Mental health, happiness and gender relations. Two other outcomes that are not used were pre-specified. The experimental design: 2 treatments (lump-sum vs installments) and 1 control program, stratified by localities (or districts) was also pre-specified. Without loss, we implemented monthly rather than pre-planned weekly installments to ensure better administrative oversight in the field.

others when the unexpected need arises. The timetable of baseline and endline activities is displayed in Figure 1. We use the administrative (transaction-level) data to calculate the 50th (75th) percentile purchase for airtime and data combined over the data period to be 188GHS (308GHS) per month. We set the total value of our communication credit intervention for each individual to 40GHS, that is, 21% of the median monthly purchase, or equivalently, 13% of the 75th percentile monthly purchase. We estimate this amount as sufficient to cover the most basic unexpected communication needs over a month or two. We first conduct three baseline survey waves prior to the deployment of the communication interventions, which include:

- **Treatment program I (Lump-sum):** individuals received 40GHS as mobile credit for one time (not discounted).[8]
- **Treatment program II (Installments):** 40GHS was split into two and individuals received this as mobile credit in installments (20GHS two times with a month interval between the two).
- **Control program:** individuals received no mobile credit.

The communication credit could be used to make a phone call, transfer airtime, visit the web, or access other social media services. After fielding the first round of interventions (lumpsum and first installment), we conducted two endline survey waves (see Figure 1). As shown in Figure 1, we started with n=1,993 individuals reachable by phone in baseline step 0 to arrive at n=1,131 eligible and select individuals in baseline step 1.

[8] At a monthly nominal discount rate of 1.16% (i.e., an annual rate of 14% in Ghana, see: https://www.bog.gov.gh/treasury-and-the-markets/interbank-interest-rates/), the net present value terms of the 20GHS installment transfers is 39.31GHS, which is around the 40GHS lumpsum transfer. Due to the short period of time (i.e., one month interval between the two 20GHS installments), we expect discounting to have little or no effect.

II.5 Treatment Assignment

We use a 1x3 factorial design, randomizing a total of 1,131 representative individuals into 3 experimental communication programs: lumpsum mobile credit (376 individuals), installments of mobile credit (371 individuals), and control program (384 individuals). We stratified based on districts, and all misfits were resolved and randomly assigned. The values of the two treatment programs are equal, as specified above. We partnered with a major telecommunications company to directly deliver the mobile credits.

II.6 Balance and Validity of Design

II.6.1 Balance

We base our treatment analysis on a comparison of individuals that received the communication treatments with those who did not receive the treatments. Successful randomization of treatments, and thus identification, requires that the assignments to treatments (i.e., lumpsum credit versus installments credit) are independent of any relevant individual-level statistics. To test that these individuals are comparable, we run the regression:

$$y_{id} = \alpha + \beta \mathbf{M}_i + \epsilon_{id}$$

on the baseline data (waves 1 and 2), where $\mathbf{M}_i = 1$ if individual i in district d received a communication credit treatment, and 0 otherwise. We consider the various treatments separately and together (pooled) for a number of different outcomes and show that individuals show no observable differences across the two groups. Tables A4 and A5 report the pre-treatment balance results and provide strong evidence in favor of randomization balance with no difference across individuals in assigned (treated) and non-assigned (control) programs.

II.6.2 Attrition

Our randomization is based on the selected individuals that draws on the baseline GLSS data files and step 0. Table 1 displays the breakdown of response rates and attrition between baselines and endlines. Here, attrition may be linked to individuals non-response and inability to reach the participants either because their phone numbers are inactive or out of network coverage area. To maximize response rates, trained field officers conducted multiple phone calls (see Figure A5) at different time horizons of the day, varying either weekdays or weekends, combined with step 0 that introduced the project and solicited the consent of the individuals. If we aggregate all the data rounds, we record an overall attrition rate of 6.5%, which is low, given the uncertainty during the pandemic. In our empirical estimations, we evaluate and formally show robustness to attrition by treatment status.

III Experiment: Results

We present and discuss the treatment effects. Since all our treatments are about communication (or mobile calling) credit provision, we first report the (combined) pooled effect of communication credit assignment, and then the separate effects for the different treatments.

III.1 Empirical Specifications

We estimate treatment effects using the model:

$$y_{idt} = \beta \mathbf{M}_{id} + \mathbf{X}_{id}' \xi + \eta_d + \mu_t + \epsilon_{idt}$$

which links various outcome(s) y_{idt} of individual i in district d at date t to the random treatment program(s) $\mathbf{M}_{id}$, district-level (stratification unit) dummies η_d, date of survey fixed effect μ_t (absorbs waves), and additional vector of controls $\mathbf{X}_{id}$ which include the baseline outcomes. For the pooled effects, $\mathbf{M}_{id}$ is a 0-1 indicator for whether an individual received any of the communication programs, and thus β captures the (pooled) treatment effect. For the separate effects, $\mathbf{M}_{id}$ is a 0-1 indicator for whether an individual received a specific communication program. We denote by β_1 and β_2 the separate treatment effects for lumpsum and installments programs, respectively (i.e., $\beta = (\beta_1, \beta_2)'$).

We take a theory-driven approach and use machine learning (specifically LASSO) to select which out of the long list of controls $\mathbf{X}_{id}$ we should include. We do this using the post-double-selection LASSO technique of Belloni et al. (2014). The post-double-selection LASSO for estimating the impacts deals with potential covariate imbalance (if any), and thus we can achieve good estimation performance, in addition to minimizing researcher degrees of freedom and the possibility for p-hacking. For our main results, standard errors are clustered at the individual level (the level of treatment) to account for arbitrary correlations (Cameron and Miller 2015). Clustering at district-level yields the same inference. To address the potential issue of multiple testing, we adjust p-values for multiple testing across the family of outcomes following the procedure presented in Romano and Wolf (2005). To evaluate and show robustness for potential attrition bias, we report Lee (2009) attrition bounds (trimming based on observed attrition rates; see Table 1), Imbens and Manski (2004) confidence sets, and Behaghel et al. (2015) attrition bounds (trimming based on the number of times individuals were called before answering the phone survey; see Figure A5).

III.2 Treatment Effects

III.2.1 Communication – Ability to Stay Connected

Do communication credit interventions matter for individuals communication? We begin by asking whether the communication programs mitigated individuals' communication constraints. Table 2 shows the pooled treatments effect for alternative communication outcomes. Relative to a control group, individuals inability to make unexpected calls for the previous 7 days decreased (-37pp = -74% of control mean), inability to make unexpected calls due to COVID-19 decreased (-17pp = -38%), unexpected need to borrow SOS airtime decreased dramatically (-22pp = -78%), and seeking digital loans decreased (3.5pp = 44%) as a result of the communication programs. Table 3 reports the separate treatment effects for each communication program. The installment program produces significantly larger mitigation of the communication constraints compared to the lumpsum (p-values < 0.01).

These results strongly confirm that the interventions mitigated individuals' binding communication barriers during the pandemic period, showing economically a large and statistically significant decrease in individuals' inability to communicate and stay connected.

III.2.2 Psychological and Economic Well-being

Do communication interventions matter for well-being? We next evaluate how the communication programs impacted the various well-being outcomes. Table 4 shows the pooled treatments effect on consumption expenditures. Table 5 displays the pooled result for mental health (measured using the Kessler Psychological Distress Scale (K10)) and domestic violence. We find null effect on total expenditures, which is reassuring since the size and specificity of our intervention were not large enough for it to be plausible to find meaningful impacts on consumption. There are, however, positive effects only for utilities and durables.[9]

In contrast to the null effect on consumption, we find meaningful impacts on psychological well-being (Table 5): mental health and domestic violence. Mental distress (measured by logK10) decreased by -9.8%. Individuals were -6.3% less likely to threaten their partners relative to the control group (Romano-Wolf p-value=0.1247 which is only significant at the 13% level), but with no effect on the likelihood of hitting their partners. Similarly, Table 6 reports the separate treatment effects, showing larger treatment effects of the installment

[9] We conducted sensitivity checks on the utilities and/or durables consumption outcomes. First, to account for outliers, we trimmed these individual consumption data at both the 1% and 5% levels. We find that the results are still significant (i.e., qualitatively similar to the untrimmed outcomes) but the effect sizes are much smaller. For utilities, the coefficient in now +3.910GHS at the 1% trimming level and +1.166GHS at 5% trimming level compared to our baseline estimate of +4.819GHS in Table 4. For durables, the coefficient in now +5.077GHS at the 1% trimming level and +0.386GHS at 5% trimming level compared to our baseline estimate of +8.575GHS in Table 4. Second, to weight the tails of these individual consumption outcomes more, we rerun the model using their log transformations (instead of their levels). Here, we find that the results are very insignificant (p-values >0.36 in all cases). We conclude that the specific effects on utilities and/or durables alone are inconclusive or indecisive. Ignoring these sensitivity checks, however, our baseline results suggest that making communication easier, as we do in the experiment, can raise the spending on durables. This is particularly interesting and relevant for policy because consumers can rely on their durable stock most of the time, and as such durable spending only adjust infrequently.

intervention on mental distress, severe mental distress (measured by K10 values > 30), and on domestic violence measures. Individuals in the installment credit are less likely (-2.3pp $\approx$ -24%) to suffer the incidence of severe mental distress and -9.7% less likely to threaten their partners (Romano-Wolf p-value=0.019 which is significant at conventional levels). There is limited effect of the lumpsum credit on severe mental distress. For consumption, the separate effects are null and indistinguishable across the two communication treatments, which is not surprising because of the the overall null pooled treatments effect on consumption expenditures (see Table 4)

For potential dynamic effects, Figures A6-A9 show the results over the trajectory survey by survey. What is significant to note is that the installment program has larger and more sustainable effects compared to the lumpsum, with the exception of consumption. This may reflect either time inconsistency or social pressure problems from receiving one-time large transfers.

IV Interpreting the Results, Heterogeneity, and the Value of Communication

IV.1 Interpreting the Results

How does communication affects well-being? We seek to understand what happens when we give mobile credit to (potentially) *communication-constrained* individuals during unexpected hardships. Conceptually, communication is a network good and could turn on at least three interesting alternative interpretations: (i) improved business-related services (via professional networks), (ii) improved social inclusion and/or protection (via social networks), and (iii) improved informal risk-sharing or consumption insurance (via social networks). We find strong empirical support for improvements in both business-related services and social inclusion, but not for informal insurance networks. We discuss and explore these alternative explanations for the communication impacts.

Professional networks operate in form of affected individuals being able to stay in touch with customers and buy/sell with vendors to increase their revenues, which we know has a positive impact on mental well-being (Ridley et al. 2020). To measure this, we asked respondents about their total hours worked for income and the amount they received from business income-related activities at endline. Treated individuals reported (insignificant) increase in their hours worked but a very significant increase in incomes (+9.0GHS per week overall) from business-related services (Table 7). This indicates that improvements in professional networks is a likely explanation.

Social inclusion (reduced isolation) operates in form of individuals being able to stay in touch with friends/family who can provide them emotional (Mullainathan and Shafir 2013) and social support, or serve as agents of social control and protection to specifically reduce domestic violence by increasing the cost of violence (à la Gelles 1983; Gelles and Straus 1979). To measure this, we asked respondents about whether they were emotionally- and socially-tired of staying at home at endline. We find very significant evidence that treated individuals were less likely to report being emotionally- and socially-tired (-31% for the lumpsum credit group; -52% for the installment credit group) but were also more likely to stay at home or seek shelter during the pandemic (Table 7). This shows that improvements in social inclusion is a meaningful, relevant explanation.

Communication credit can improve or rejuvenate informal insurance arrangements. In vulnerable periods such as COVID-19 related lockdowns, households might have difficulty communicating with their informal insurance networks (family, friends) and thus consumption risk-sharing ability may suffer (Blumenstock, Eagle and Fafchamps 2016; Jack and Suri 2016). The provision of mobile credit might alleviate that constraint. We take advantage of our individual-level panel data on consumption to measure this using changes in consumption growth at endline. The pandemic's lockdown was a negative consumption shock (see Figure A10): individuals located in lockdown areas show a large decrease in consumption growth (median=-13%; mean=-45%) compared to those in non-lockdown areas (median=-8%; mean=-27%). Yet, we do not find evidence for an impact of mobile credit on the negative consumption effect of the lockdown (Table 7). Our test on consumption insurance here (which is similar to the one in Cochrane 1991) regresses consumption growth against the negative consumption shock (ie., lockdown) combined with mobile credit (i.e., communication intervention). This result suggests that improvements in informal insurance networks, while plausible, is unlikely at play.

Finally, we note that the two channels we find evidence for –i.e., improved business networks and social inclusion/protection – are also consistent with Béland et al. (2021) who used the Canadian Perspective Survey Series during the COVID-19 pandemic to document that concerns about both finances and maintaining social ties are significantly related to concerns about family stress and domestic violence.

IV.2 Heterogeneous Effects

The analyses so far assume that the effects of the communication intervention are uniform. Here, examine heterogeneity in treatment effects along four dimensions: (i) poverty, (ii) informality, (iii) gender, and (iv) lockdown. The results are shown in Tables A6-A9. The decrease in domestic violence is more significant for the very poor, while individuals in the informal sector experienced significantly larger and better mental health improvements. Conversely, females experienced slightly better mental health effects but this is not statistically significant, while individuals located in previously locked-down areas are more eager to re-allocate their budgets to more consumption (specifically, to utilities and durables, as expected). The latter reflects individuals who might still be battling the persistent economic impacts of the COVID-driven lockdowns.

The results on gender differences in domestic violence and mental health/stress are worth discussing. Table A8 indicates that females are about -12% (=(-0.14/1.16)x100) relatively less likely to hit their partner, but when combined with mobile credit, there is no significant difference in hitting a partner by gender. Similarly, when the mobile credits intervention is combined with mental health, we see no significant differences by gender. From the raw data and on a scale of 1 (never) to 4 (very often), men reported an average score of 1.15 hitting their partners versus females who reported an average score of 1.09 hitting their partners (p-value=0.124 from a t-test of their difference). Mental health was equally high, with an average score of 14.47 for males and 14.55 for females. (p-value=0.124 from a t-test of their difference). These unconditional means from the data are consistent with the coefficients on female in Table A8. Béland et al. (2021) show that stress and domestic violence were high during the pandemic for both men and women, which is consistent with summary statistics from our raw data.

We interpret the lack of gender differences in mental stress or domestic violence when combined with mobile credits within the lens our Framework on channels, suggesting that mobile credit, in our context, either reduces isolation and increase the cost of hitting your partner or allows you to stay in touch with your business clients, thereby minimizing mental stress and the potential to hit your partner if engaged in business activities. These results are in the right direction, and thus reassuring and provide corroborative support for our main findings.

IV.3 Discussions

We document the well-being impacts of providing low-cost in-kind communication transfers. A natural question is *how does such in-kind transfers compare to cash transfers?* Our experiments did not include a separate treatment program for cash, but one can draw some insights from the ongoing large literature on cash transfers during the pandemic (see e.g., Banerjee et al. 2020). In rural Kenya, Banerjee et al. (2020) examined the effects of a Universal Basic Income (UBI) during the COVID-19 pandemic using a large-scale experiment, showing moderate to no improvements on mental health measures. For context, their cash interventions transferred \$0.75 per day (amounting to a non-discounted total of about \$23.3 per month) to the beneficiaries, which is much larger than the cash equivalence of our in-kind communication transfers, yet we find meaningful improvements on our mental health measures. We do not find any impact on food consumption (Table 4) and therefore no impact is likely to be found on hunger, but Banerjee et al. (2020) reported modest UBI improvements on food consumption (meat/fish) and hunger. Thus, it seems communication transfers might yield larger improvements in mental health relative to cash transfers.

IV.4 The Value of Communication

To put our causal estimates into context, we consider the cost-effectiveness of a policy that *provides communication credit to low-income adults for two months*. To compare the cost of this policy that provides communication transfers with the associated benefits, we adapt Hendren and Sprung-Keyser (2020)'s cost-benefit framework that is conducive to empirical welfare analysis. Specifically, we calculate the marginal value of public funds (MVPF), which estimates the ratio of society's willingness to pay for the provision of communication credit to the net cost to the government (here, an "imagined" funder) of implementing this policy.

We estimate society's willingness to pay (MVPF's numerator) to include two main components. First, is the averted (otherwise) social cost of mental health burden, ξ. We assume mental health disorders account for 13% of disease burden (Adhvaryu et al. 2019). With a health expenditure per capita of US\$78 in Ghana (World Bank 2018), and a treatment effect of -10% reduced mental destress rate, we conservatively estimate the averted social cost of mental health burden to be ξ = 0.10x0.13xUS\$78=+US\$1.014. Our ξ estimate is very conservative in comparison to Addo et al. (2013) that would have implied a +US\$2.68 averted social cost (2.6 times larger). Second, is the individual beneficiary's willingness to pay for not visiting the hospital or not getting mentally unwell, η, which includes three sub-component estimates: (i) out-of-pocket health bill (η_1 =+US\$0.82); (ii) travel cost to health centers (η_2=+US\$0.203), and (iii) lost income from missed work (η_3=+US\$11.55). Together, the MVPF's numerator = $\xi+\sum_{i=1}^{3}\eta_i$=US\$13.590 for the average treated individual. We drop the direct value of the communication subsidy to beneficiaries (+US\$7.0) to avoid double counting.

Next, we estimate the net cost to the "imagined" funder or government (MVPF's denominator) to include two main components. First, is the cost of providing communication transfer for two months, G (=+US\$7.0). Second, is the missed communication services tax (CST) revenue if individuals do not communicate or stay connected, μ. In Ghana, the CST is used to finance the National Youth Employment Programme (NYEP) ($\geq$20% of the CST) and support other national development activities. Using the prevailing 5% CST rate (Ghana Revenue Authority 2020), we estimate that the government loses 0.05xUS\$7.0= -US\$0.35. We intentionally over-estimate the total cost of this policy: (i) communication is a network good so the ultimate economic incidence of these communication transfers extends to other individuals – others might benefit from receiving mobile phone calls from the treated individual (positive externalities). Arguably, such positive externalities dominate the potential congestion hassle or traffic on the communication network (negative externalities) (Björkegren 2019 provides an example in Rwanda). (ii) We conservatively did not factor in the reduced fiscal cost from less hospital visits due to the reduced likelihood of mental health disorders and/or domestic violence. Together, the MVPF's denominator = $G+\mu$=US\$6.65 for the average treated individual.

Finally, taking the ratio, we estimate a conservative MVPF of providing communication credit to be $\frac{13.590}{6.650} = 2.044$. This suggest that US\$1.0 of spending on this communication credit policy delivers more than US\$1.0 in benefits to its beneficiaries. Alternatively, the MVPF estimate implies that US\$1 of expenditure yields US\$2 of total benefits, and so generates US\$1 of net benefits. At the aggregate level, the policy's total benefit will be US\$54,035,343 against a total cost of US\$26,441,135. Notice that in determining the MVPF, we intentionally bias the estimates to understate the benefits and overstate the costs (Appendix section VI.8 contains additional details).

V Conclusion

The COVID-19 pandemic uncovered a great deal of economic and mental health crises, most particularly for those people bound by credit, savings and psychological constraints. This paper provides new experimental evidence on the impact of providing communication transfers. Communication during pandemics meaningfully matters for well-being. Our mobile credit interventions led to a notable decrease in unexpected communication constraints; individuals were better able to mitigate their inability to meet unexpected communication needs and stay connected. As a result, the programs led to meaningful well-being improvements, particularly on mental health, but modestly on domestic violence, and null on overall consumption expenditures. We present evidence that improvements in both business-related services and social inclusion/ protection are relevant channels explaining the estimated communication impacts.

In terms of policy and design, communication initiatives that relax potential communication constraints improve psychological well-being and, to a modest degree, reduce domestic violence. However, these programs are more valuable if implemented in numerous installments of communication transfers, rather than one-time. Simple cost-benefit analysis shows that providing communication credit to low-income adults is a cost-effective policy for improving mental health. There is almost no work linking mental health and information and communications technology (ICT) (Jensen 2007; Blumenstock, Eagle and Fafchamps 2016). We offer a short-run causal view of what communication does to mental health, using evidence from an unexpected pandemic.

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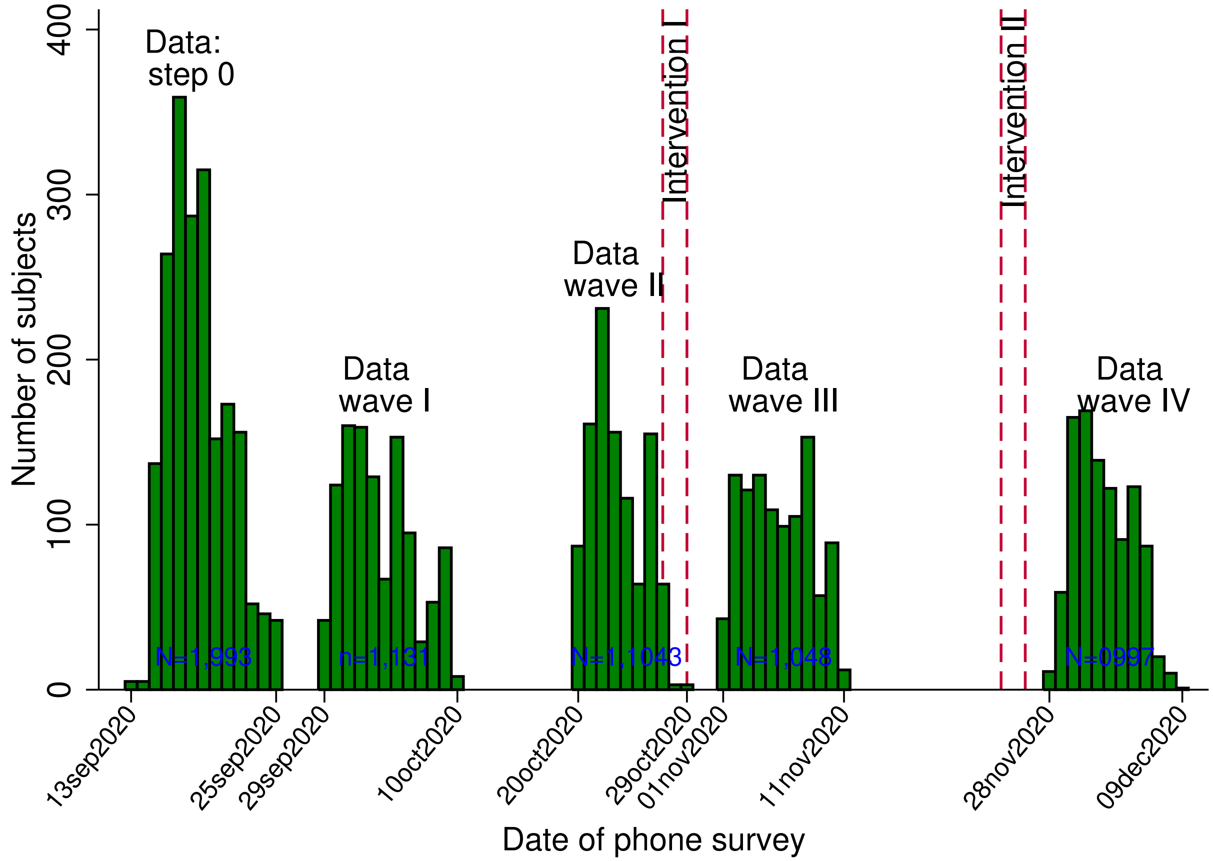
Main Results for Text

Figure 1: **Data collection and timetable**



Note: Figure shows the timetable of baseline and endline data collection activities. The various bars reflect the daily number of phone calls or individuals surveyed. The baseline involves three panel survey waves (step 0, wave I and wave II). These waves provide information to determine eligible individuals and to conduct pre-intervention randomization balance tests. The endline involves two panel waves (wave III and wave IV) that follow the first round of interventions deployment (Intervention I). Intervention I (the lumpsum and the first tranche of credit installment) spans October 27-29, 2020. Intervention II (the second tranche of credit installment) spans November 24-26, 2020. A lockdown was announced on March 30, 2020 and removed on April 20, 2020. The cumulative number of confirmed COVID-19 cases in Ghana as of September 13, 2020 (the start of our experiment) was 45,434. This increased to around 52,738 as of December 9, 2020 (the end of our experiment). https://www.statista.com/statistics/1110892/coronavirus-cumulative-cases-in-ghana/

Table 1: **Attrition**

	Lumpsum	Installments	Control	Total	Attrition
STEP 0				1,993	
Verify phone numbers					
Measure poverty (Schreiner 2005)					
SELECT SAMPLE (Randomized)	376	370	384	1130	
BASELINE I (Wave 1)	376	370	384	1130	0
	(100%)	(100%)	(100%)	(100%)	(0%)
	(0%)	(0%)	(0%)	(0%)	(0%)
BASELINE II (Wave 2)	352	340	351	1043	87
	(94%)	(92%)	(91%)	(92%)	(8%)
	(24%)	(27%)	(28%)	(27%)	(27%)
ENDLINE I (Follow-up wave 3)	355	344	349	1048	82
	(94%)	(93%)	(91%)	(93%)	(7%)
	(23%)	(26%)	(29%)	(26%)	(26%)
ENDLINE II (Follow-up wave 4)	343	335	319	997	133
	(91%)	(91%)	(83%)	(88%)	(12%)
	(28%)	(29%)	(38%)	(32%)	(32%)

Note: Table reports the summary statistics for the subsample that was successfully reached for a follow-up and for the subsample that was not successfully reached in endline phone surveys. Shown for all panel waves.

Table 2: **Mitigation of communication constraints**

	Unable to Call, 7days 0-1		Unable to Call, COVID19 0-1		Borrow SOS Airtime 0-1		Seek Digital Loan 0-1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Communication Credit (β)	-0.371***	-0.357***	-0.194***	-0.172***	-0.226***	-0.221***	-0.034**	-0.035**
	(0.024)	(0.021)	(0.026)	(0.021)	(0.018)	(0.019)	(0.012)	(0.012)
Observations	2045	2018	2045	2018	2045	2018	2045	2018
District FE	No	Yes	No	Yes	No	Yes	No	Yes
Survey Date FE	No	Yes	No	Yes	No	Yes	No	Yes
Controls	None	PD Lasso	None	PD Lasso	None	PD Lasso	None	PD Lasso
Mean of dep. variable (control)	0.499	0.499	0.452	0.452	0.289	0.289	0.079	0.079
Lee 2009 Attrition Bounds	[-0.425; -0.364]		[-0.240; -0.179]		[-0.283; -0.222]		[-0.079; -0.031]	
Imbens-Manski 2004	[-0.458; -0.336]		[-0.273; -0.149]		[-0.314; -0.198]		[-0.093; -0.015]	
p-value: Romano-Wolf Correction	0.002		0.002		0.002		0.008	

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the individual $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). 90% confidence sets (CS) around attrition bounds are reported in brackets. Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported for communication outcomes family (Unable to Call, 7days 0-1; Unable to Call, COVID19 0-1; Borrow SOS Airtime 0-1; Seek Digital Loan 0-1). Behaghel et al. (2015) attrition bounds (not reported) are tighter.

Table 3: **Mitigation of communication constraints**

VARIABLES	(1) Unable to Call 7days 0-1	(2) Unable to Call COVID19 0-1	(3) Borrow SOS Airtime 0-1	(4) Seek Digital Loan 0-1
Lumpsum Credit (β_1)	-0.282***	-0.119***	-0.184***	-0.0237*
	(0.0239)	(0.0244)	(0.0200)	(0.0134)
Installments Credit (β_2)	-0.439***	-0.225***	-0.265***	-0.0461***
	(0.0225)	(0.0240)	(0.0191)	(0.0131)
Observations	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	0.499	0.452	0.289	0.079
p-value for test: $\beta_1 = \beta_2$	0.000	0.000	0.000	0.002
Lee 2009 Attrition Bounds β_1	[-0.108; -0.069]	[-0.038; 0.001]	[-0.089; -0.049]	[-0.034; 0.005]
Lee 2009 Attrition Bounds β_2	[-0.310; -0.289]	[-0.198; -0.177]	[-0.190; -0.169]	[-0.057; -0.036]
Imbens-Manski 2004 CS β_1	[-0.138; -0.043]	[-0.070; 0.030]	[-0.114; -0.030]	[-0.056; 0.020]
Imbens-Manski 2004 CS β_2	[-0.338; -0.268]	[-0.230; -0.149]	[-0.215; -0.153]	[-0.079; -0.023]
p-value: Romano-Wolf Correction β_1	0.010	0.010	0.010	0.139
p-value: Romano-Wolf Correction β_2	0.010	0.010	0.010	0.010

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). 90% confidence sets (CS) around attrition bounds are reported in brackets. Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported for communication outcomes family (Unable to Call, 7days 0-1; Unable to Call, COVID19 0-1; Borrow SOS Airtime 0-1; Seek Digital Loan 0-1). Behaghel et al. (2015) attrition bounds (not reported) are tighter. See Appendix section VI.7 for variable definitions.

Table 4: **Impacts of communication programs on consumption expenses**

VARIABLES	(1) Total (GHS) Expenditure	(2) Food-In (GHS)	(3) Food-Out (GHS)	(4) Utilities (GHS)	(5) Personal care (GHS)	(6) Educ. (GHS)	(7) Health (GHS)	(8) Durables (GHS)
Communication Credit (β)	12.93	-6.106	2.081	4.822***	1.778	1.125	-4.253	8.578***
	(9.936)	(5.784)	(3.790)	(1.707)	(2.102)	(2.007)	(3.343)	(2.702)
Observations	2,018	2,018	2,018	2,018	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	219.573	125.789	45.952	8.298	8.299	6.943	21.985	2.307
Lee 2009 Attrition Bounds	[-26.423; 24.893]	[-22.276; 0.426]	[-9.991; 7.319]	[-3.340; 5.251]	[-2.646; 3.171]	[-6.296; 1.680]	[-13.573; -1.858]	[-1.426; 9.094]
Imbens-Manski 2004 CS	[-40.599; 37.968]	[-29.701; 7.406]	[-15.276; 11.895]	[-5.524; 7.454]	[-4.842; 5.435]	[-8.295; 4.308]	[-17.587; 2.487]	[-3.178; 11.415
p-value: Romano-Wolf Correction	0.584	0.524	0.584	0.098	0.454	0.600	0.600	0.004

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject × date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). 90% confidence sets (CS) around attrition bounds are reported in brackets. Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported for consumption expense outcomes family (Total (GHS) Expenditure; Food-In (GHS); Food-Out (GHS); Utilities (GHS); Personal care (GHS); Educ. (GHS); Health (GHS); Durables (GHS)). Behaghel et al. (2015) attrition bounds (not reported) are tighter.

Table 5: **Impacts of communication programs on mental health and domestic violence**

	Threatened Partner 1-4		Hit Partner 1-4		log K10		Severe Distress 0-1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Communication Credit (β)	-0.068	-0.078*	-0.026	-0.044	-0.112***	-0.097***	-0.004	-0.004
	(0.036)	(0.033)	(0.034)	(0.032)	(0.015)	(0.013)	(0.008)	(0.007)
Observations	2045	2018	2045	2018	2045	2018	2045	2018
District FE	No	Yes	No	Yes	No	Yes	No	Yes
Survey Date FE	No	Yes	No	Yes	No	Yes	No	Yes
Controls	None	PD Lasso	None	PD Lasso	None	PD Lasso	None	PD Lasso
Mean of dep. variable (control)	1.247	1.247	1.166	1.166	2.704	2.704	0.025	0.025
Lee 2009 Attrition Bounds	[-0.198; -0.057]		[-0.159; -0.017]		[-0.148; -0.112]		[-0.025; -0.003]	
Imbens-Manski 2004	[-0.238; -0.015]		[-0.199; 0.024]		[-0.168; -0.094]		[-0.033; 0.006]	
p-value: Romano-Wolf Correction	0.129		0.634		0.010		0.634	

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). 90% confidence sets (CS) around attrition bounds are reported in brackets. Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported for mental health and domestic violence outcomes family (Threatened Partner 1-4; Hit Partner 1-4; log K10; Severe Distress 0-1). Behaghel et al. (2015) attrition bounds (not reported) are tighter.

Table 6: **Impacts of communication programs on well-being measures**

VARIABLES	(1) Total (GHS) Expenditure	(2) Threatened Partner 1-4	(3) Hit Partner 1-4	(4) log K10	(5) Severe Distress 0-1
Lumpsum Credit (β_1)	10.63	-0.0431	-0.0194	-0.0568***	0.0122
	(11.36)	(0.0374)	(0.0372)	(0.0143)	(0.00844)
Installments Credit (β_2)	17.75	-0.121***	-0.0794**	-0.139***	-0.0227***
	(11.82)	(0.0399)	(0.0383)	(0.0142)	(0.00610)
Observations	2,018	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	219.573	1.247	1.166	2.704	0.025
p-value for test: $\beta_1 = \beta_2$	0.314	0.010	0.100	0.000	0.000
Lee 2009 Attrition Bounds β_1	[-18.916; 16.809]	[-0.084; 0.031]	[-0.080; 0.035]	[-0.022; 0.009]	[-0.011; 0.028]
Lee 2009 Attrition Bounds β_2	[-15.773; 7.861]	[-0.171; -0.087]	[-0.137; -0.053]	[-0.134; -0.120]	[-0.033; -0.031]
Imbens-Manski 2004 CS β_1	[-33.491; 30.054]	[-0.117; 0.073]	[-0.112; 0.076]	[-0.045; 0.027]	[-0.031; 0.039]
Imbens-Manski 2004 CS β_2	[-32.234; 21.343]	[-0.254; -0.046]	[-0.220; -0.012]	[-0.154; -0.103]	[-0.040; -0.024]
p-value: Romano-Wolf Correction β_1	0.584	0.584	0.970	0.010	0.257
p-value: Romano-Wolf Correction β_2	0.376	0.020	0.267	0.010	0.020

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** $p<0.01$ (1% level), ** $p<0.05$ (5% level), * $p<0.1$ (10% level). 90% confidence sets (CS) around attrition bounds are reported in brackets. Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported separately for consumption expense outcomes family (Total (GHS) Expenditure; Food-In (GHS); Food-Out (GHS); Utilities (GHS); Personal care (GHS); Educ. (GHS); Health (GHS); Durables (GHS)), and for mental health and domestic violence outcomes family (Threatened Partner 1-4; Hit Partner 1-4; log K10; Severe Distress 0-1). Behaghel et al. (2015) attrition bounds (not reported) are tighter. See Appendix section VI.7 for variable definitions.

Table 7: **Explaining the impacts of communication programs**

VARIABLES	(1) Professional/Business Networks: Hours worked (last 7 days) (Hrs)	(2) Professional/Business Networks: Business Income (last 7 days) (GHS)	(3) Social Inclusion/ Networks: Emotionally -Tired 0-1	(4) Social Inclusion/ Networks: Stayed Home (last 5 weeks) 0-1	(5) Insurance Networks: Consumption Growth (%)
Lumpsum Credit (β_1)	0.834	9.715*	-0.159***	0.116***	-20.26***
	(0.561)	(5.142)	(0.0283)	(0.0331)	(6.583)
Installments Credit (β_2)	-0.289	8.365*	-0.265***	0.273***	7.381
	(0.615)	(4.977)	(0.0280)	(0.0372)	(6.657)
Locked-down 0-1, [Consumption shock]					-84.73***
					(32.27)
Observations	2,018	2,018	2,018	986	906
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	18.126	59.117	0.519	0.257	-29.741
p-value for test: $\beta_1 = \beta_2$	0.120	0.106	0.000	0.000	-
p-value: Romano-Wolf Correction β_1	0.188	0.188	0.010	0.059	0.188
p-value: Romano-Wolf Correction β_2	0.604	0.158	0.010	0.030	0.277
Interactions	-	-	-	-	-
Lumpsum Credit	-	-	-	-	-6.482
x Locked-down 0-1 δ_1	-	-	-	-	[16.084]
Installments Credit	-	-	-	-	-3.157
x Locked-down 0-1 δ_2	-	-	-	-	[16.343]
p-value: Romano-Wolf Correction δ_1	-	-	-	-	0.851
p-value: Romano-Wolf Correction δ_2	-	-	-	-	0.970
p-value: Romano-Wolf Correction Lockdown	-	-	-	-	0.743
p-value for test: $\delta_1 = \delta_2$	-	-	-	-	0.920

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject × date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). Romano-Wolf [2005] multiple hypothesis correction *p*-values reported for all communication network outcomes family (professional, social, and informal insurance).

VI Appendix

VI.1 Global Review of Communication Programs – Motivating Evidence I

Table A1: **A Global review of COVID-19 communication interventions**

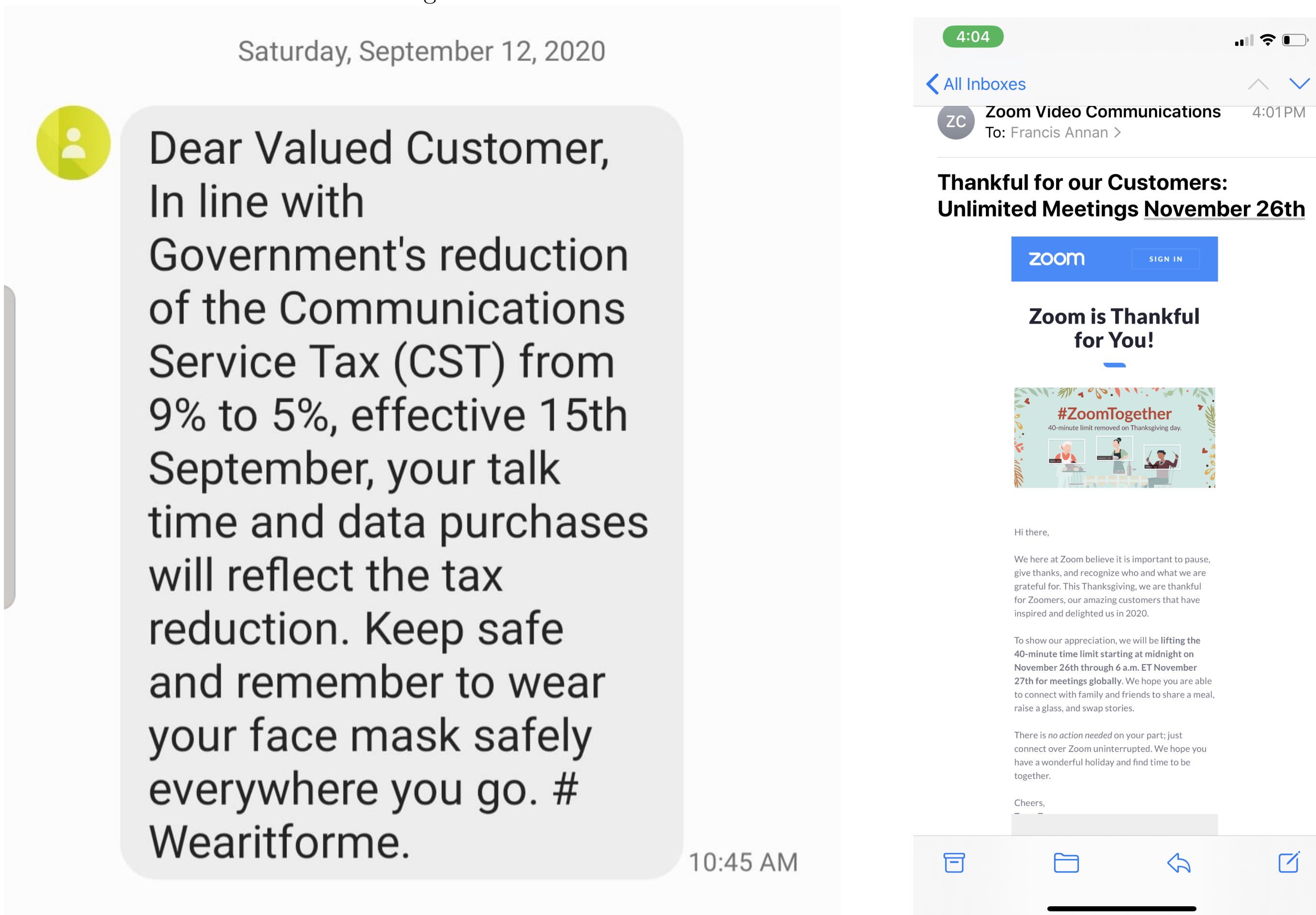
Setting	Entity	Details and source(s)	Date started	Date ended
United States	Government **FCC**	*FCC launched the program Keep Americans Connected in which communications companies agreed on not terminating the internet services of Americans in case they do not keep up to date with payments of internet and telephone bills in response to the COVID-19 crisis. The companies opened their Wi-fi hotspots for the population.	03/13/2020	06/30/2020
		*FCC also maintained other communication initiatives during the pandemic such as granting ATT to use additional spectrum in Puerto Rico and Virgin Islands in order to improve and expand the internet connectedness in these territories (60 days period).	03/26/2020	05/25/2020
		*FCC waived temporarily its rules to Inteliquent to Zoom and WebEx in order to stimulate and help consumers who now need strictly in these services to study and work. **Source:** https://www.fcc.gov/keep-americans-connected	03/27/2020	06/30/2020
	Companies	**ATT Inc.:** *Provided free 10GB of internet data per month for 60 days as a temporary relief to eligible customers to be able to stay connected during the difficult times, starting March 27, 2020. **Source:** https://about.att.com/newsroom/2020/covid_19_att_prepaid.html	03/27/2020	05/26/2020
		Comcast Corp.: Provided essential internet and mobile services without charge to low-income families, including seniors, veterans and people with disabilities in the United States. **Source:** https://corporate.comcast.com/covid-19	Not available	Not available
		Amazon: *Donated 8,200 laptops to students who attend public schools in Seattle and 4,000 laptops for high school students across the US through the Amazon Future Engineer program.	04/06/2020	–
		*Made many videos on Amazon Prime free for anyone during the stay at home orders period. Content included cartoons and family friendly movies. In addition to that, Amazon made many of its books free for the public who could download them as PDFs. **Source:** https://www.aboutamazon.com/news/company-news/amazons-covid-19-blog-updates-on-how-were-responding-to-the-crisis	03/04/2020	Not available
		Microsoft: *Microsoft has supported the local education of Washington state during the Pandemic by making the Virtual Classroom and Teams available for free. It has also created training sessions for teachers of the state and helped schools in the districts to increase their phone lines to accommodate more parents and studentsâ phone calls. *Microsoft is also working with the Washington stateâs government to build more broadband spots around the state to help more people have access to the internet through the Airban initiative. The company also brought emergency coverage to 29 school districts of the state. **Source:** https://news.microsoft.com/on-the-issues/2020/04/17/microsoft-covid-19-washington-state/	03/16/2020	Not available
Ghana	Government	The Government reduced the Communication Service Tax (CST) from 9pct to 5pct which reflected a reduction in the cost of mobile talk time and data purchases, effective September 15, 2020 in response to COVID-19 **Source:** https://gra.gov.gh/domestic-tax/tax-types/communication-service-tax/	09/15/2020	Ongoing
Brazil	Government	*The government signed an agreement with Cisco in late May in order to launch the program âBrasil Digital e Inclusivoâ (Digital and Inclusive Brazil) that has as its goal to accelerate the technological and digital development of the country. As a response to the COVID-19 crisis, the program aims to facilitate and accelerate telemedicine in the country.	05/27/2020	Ongoing
		*13.6 million of Brazilians live in the âfavelasâ (slums) and usually have restricted access to technology and communication systems. In this way, in order to bring awareness about the pandemic to the most vulnerable in Brazil, NGOs, journalists and activists have used alternative methods of communication in the population.	03/DD/2020	Ongoing
		*The Brazilian government launched a program to distribute technological equipment and access to the internet for students of the public school system in the country. The initiative will cost approximately R2.5$billionsandtheBrazilianAgencyofCommunications(Anatel)willberesponsibletoimplementitand$ distribute the materials. **Source:** https://newsroom.cisco.com/feature-content?type=webcontent&articleId=2076852	09/18/2020	Ongoing
Ecuador	Government	Similar to the most Favelas communities in Brazil, Ecuador also has a significant population that has limited access to technology and communication channels. These are indigenous communities in which the government and other organizations such as UNESCO have approached in regards to the pandemic in a very strategic way. They have been taking advantage of the communication channels that the indigenous communities have even though they are very scarce. Webpages directed to these communities that address COVID were created, audios and videos were produced by UNESCO and the organizations as well as others have been conducting cultural activities with the communities in order to bring awareness and information about the pandemic. **Source:** https://en.unesco.org/news/media-and-communications-indigenous-peoples-pandemic	03/DD/2020	Not available
Global /United States	Company- **Zoom**	**ZoomTogether** Zoom removed the 40 minutes time limit for free accounts during Thanksgiving as an initiative to help families and friends communicate during the holiday season even if they were distant to each other During Thanksgiving Day, anyone was able to make video conferences longer than 40 minutes through Zoom without being interrupted. **Source 1:** https://www.cnn.com/2020/11/17/tech/zoom-time-limit-thanksgiving-trnd-wellness/index.html	11/26/2020	11/27/2020

Table A2: **CONT'D: A GLOBAL REVIEW OF COVID-19 COMMUNICATION INTERVENTIONS**

Setting	Entity	Details and source(s)	Date started	Date ended
Global	Company- **Google**	*Google has donated USD10 million for Distance Learning Fund that supports organizations across the globe which help students who have had to adapt to online learning but do not have access to resources to do so	03/DD/2020	-
		*Google has also partnered with many universities around the world and distributed AI tools and mechanisms to help them keep track of the development of COVID-19 in the world and spread information about it for all. **Source 1:** https://www.google.org/covid-19/#distance-learning **Source 2:** https://blog.google/outreach-initiatives/google-org/google-supports-covid-19-ai-and-data-analytics-projects/	03/DD/2020	Not available
Global	Company- **Transperfect**	*Transperfect has been translating and delivering materials and information about COVID-19 across the globe. The work has been so helpful that the company won the International Business Award for COVID-19 Communication Initiatives. *The company produced videos of COVID-19 prevention tips in more than 11 languages and personalized it for companies for free. **Source:** https://www.prnewswire.com/news-releases/transperfect-wins-international-business-award-for-covid-19-communications-initiatives-301134747.html	04/DD/2020	Not available
Europe and United States	Companies- **Netflix, Youtube, Streaming services**	These companies have been slowing down and decreasing the streaming quality of their videos since March in Europe and also in the US. The initiative is an attempt to help with the internet traffic and higher latency and packet loss caused by the high usage of the internet by households after stay at home orders took place in Europe and in the US (30 days period). **Source 1:** https://www.cnn.com/2020/03/19/tech/netflix-internet-overload-eu/index.html **Source 2:** https://latest-news-viral.blogspot.com/2020/03/streaming-in-time-of-covid-19-youtube.html	04/01/2020	04/30/2020
Global /India	Company- **Facebook**	*Facebook has been partnering with governments in order to spread accurate information about the pandemic. An interesting and important partnership was with Indiaâs government that has been relying a lot on social media in order to spread awareness and information about COVID-19. Other than social media, Indian local governments have also developed and used apps that monitor COVID-19 in the country, by using Information and Communications Technology (ICT) and Artificial Intelligence (AI). *These apps are helpful and very informative, but a significant part of the population in India does not have access to the internet which shows how the Digital Divide in India has deepened the social, health and educational inequalities in the country. **Source 1:** https://about.fb.com/news/2020/11/coronavirus/; **Source 2:** https://www.bbc.com/news/world-asia-india-53471749 **Source 3:** https://www.weforum.org/agenda/2020/10/how-covid-19-deepens-the-digital-education-divide-in-india/ **Source 4:** https://academiccommons.columbia.edu/doi/10.7916/d8-bbw6-yt70 *Download the paper to see all the apps created* **Source 5:** https://www.weforum.org/agenda/2020/10/how-covid-19-deepens-the-digital-education-divide-in-india/	03/DD/2020	Not available

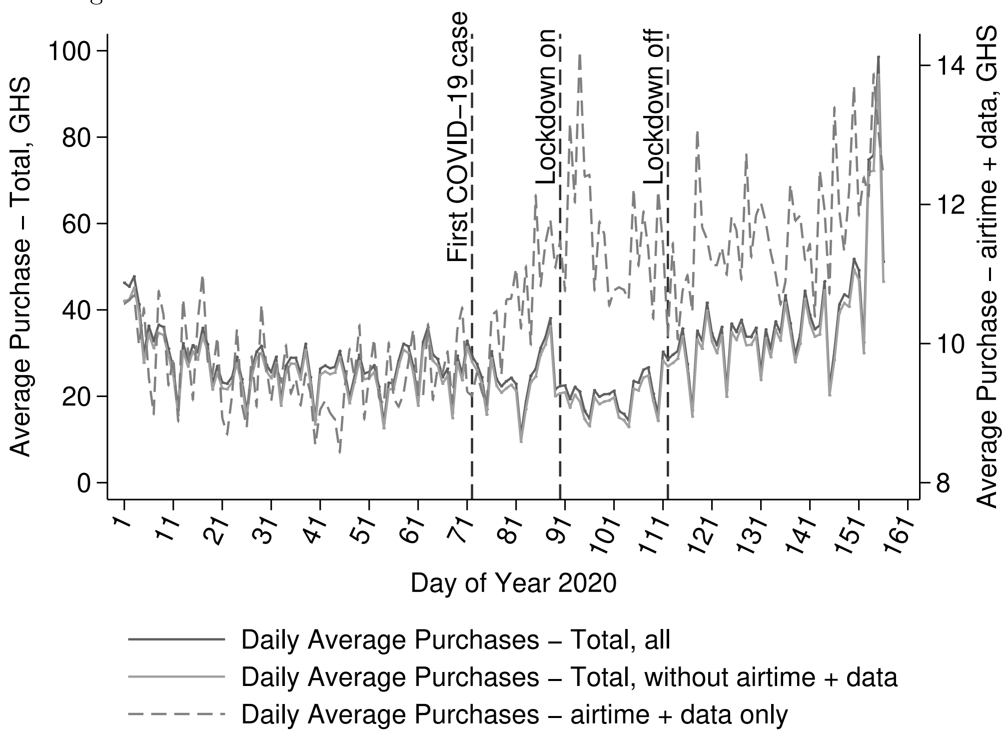
VI.2 Exhibits – Motivating Evidence II

Figure A1: Communication programs



VI.3 Administrative Data – Motivating Evidence III

Figure A2: **Mobile financial transactions during COVID-19**



Note: Mobile financial transaction data from a major local telecommunications company and based on 694,695 transactions (2,0751 random unique subscribers). As displayed, average purchase (total and total without airtime + data) shown in the left vertical axis with solid lines, while average purchase for airtime-related activities (airtime + data only) shown in the right vertical axis with a dash line. Overall market activity decreased following the onset of the pandemic, but demand for mobile airtime-related activities sharply increased over the period. Pre-COVID-19, these two purchases (average totals versus average airtime) look similar.

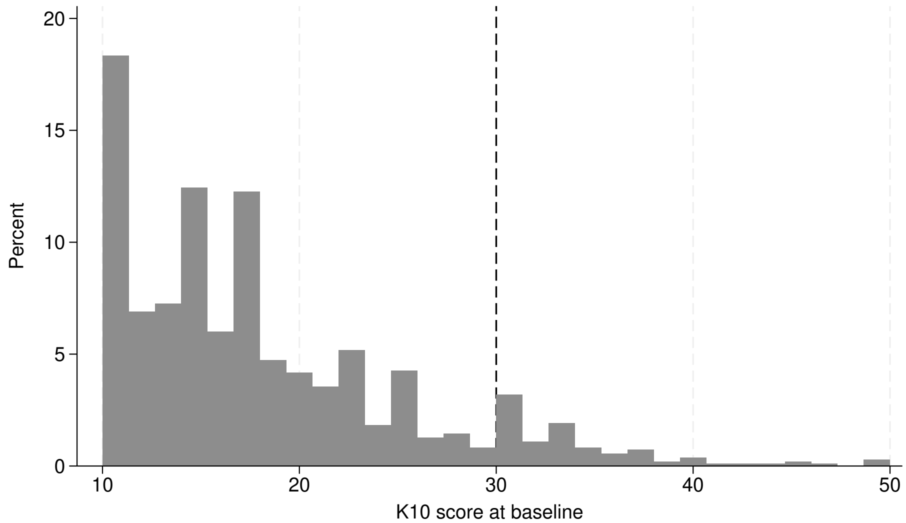
VI.4 Descriptive Statistics

Table A3: Summary statistics of relevant variables

Variable	Mean	SD	N
Demographic Characteristics			
Female 0-1	0.147	0.354	1,130
Akan ethnic 0-1	0.363	0.481	1,130
Married 0-1	0.911	0.285	1,130
Attained Junior High School (JHS) 0-1	0.784	0.412	1,130
Household size (number)	6.907	4.088	1,107
Self-employed 0-1	0.763	0.426	1,130
Operates in informal sector 0-1	0.800	0.400	1,130
Personal income (1 to 5 scale) (monthly)	1.622	0.898	1,105
Staying together with mother 0-1 (Wave 0)	0.067	0.251	1,130
Has no religion 0-1 (Wave 0)	0.054	0.226	1,130
Staying together with spouse 0-1 (Wave 0)	0.869	0.338	1,130
Age at marriage (Years) (Wave 0)	24.935	4.971	1,083
Poverty			
Poverty rate (%) (Schreiner 2005) (Wave 0)	22.043	20.534	1,130
Pandemic Basics			
Aware of COVID-19 0-1	0.996	0.060	1,105
Trust Government's estimates about COVID-19 0-1	0.799	0.401	1,105
In previously lockdown region 0-1	0.183	0.387	1,130
Self does housework during pandemic 0-1	0.168	0.374	1,105
Has relocated / moved in past 7 days 0-1 (Wave 2)	0.014	0.119	977
Key Communication Constraints			
Need to connect increased due to pandemic 0-1	0.701	0.458	1,104
Unable to call in past 7 days 0-1	0.627	0.484	1,103
Unable to call due to COVID-19 0-1	0.549	0.498	1,104
Unable to make airtime transfers in past 7 days 0-1	0.474	0.500	1,103
Borrow airtime 0-1 (Wave 2)	0.319	0.466	977
Seek digital loan 0-1 (Wave 2)	0.088	0.283	977
Well-being Measures			
Total Expenditure (GHS) (weekly)	324.112	423.254	1,102
Threatened Partner (1 = never to 4 = very often)	1.194	0.701	1,102
Hit Partner (1 = never to 4 = very often)	1.134	0.670	1,102
log K10	2.820	0.369	1,102
Severe Distress 0-1	0.096	0.295	1,102
I'm tired (mentally, emotionally, or socially) of COVID-19 0-1	0.539	0.499	1,104
I'm depressed (1 = disagree to 5 = agree)	1.600	0.942	1,102
I'm relaxed (1 = disagree to 5 = agree)	2.885	1.384	1,102
I'm satisfied with life, all else equal (1 = disagree to 5 = agree)	2.536	1.318	1,102
I'm satisfied with finances, all else equal (1 = disagree to 5 = agree)	2.074	1.157	1,102

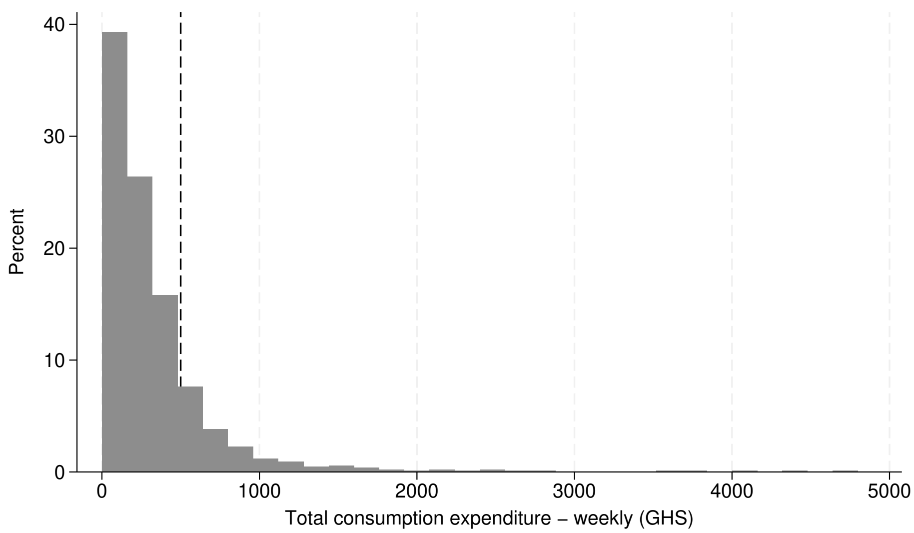
Note: Observations are at the individual level. Table reports the summary statistics of relevant variables from our baseline survey waves. This include information about demographics, poverty indicators, communication and well-being outcomes, respectively. The exchange rate during the baseline period is US$ 1.0 = GHS 5.80.

Figure A3: **K 10 score at baseline (wave 1)**



Note: Observations are at the individual level. Low (scores of 10-15, indicating little or no psychological distress). Moderate (scores of 16-21). High (scores of 22-29). Very high or severe distress (scores of 30-50). 11.5% rate of severe distress (indicated by the vertical dashed line).

Figure A4: **Total consumption expenditure at baseline (wave 1)**



Note: Observations are at the individual level. Total consumption expenditure sums all expenses: food (inside and outside home), utilities, personal care, education, health, and durables. 81.7% rate of poor consumption ($\leq$ 500GHS per week and indicated by the dashed vertical line).

VI.5 Balance

Table A4: **Balance test: pre-intervention treatment-control differences**

Variable	Constant	Lumpsum	Installments
Communication Measures (Wave 1)			
Unable to call in past 7 days 0-1	0.632***	-0.016	0.002
	(0.026)	(0.035)	(0.035)
Unable to call due to COVID-19 0-1	0.565***	-0.006	-0.044
	(0.028)	(0.037)	(0.039)
Borrow airtime 0-1 (Wave 2)	0.297***	0.029	0.040
	(0.028)	(0.037)	(0.036)
Seek digital loan 0-1 (Wave 2)	0.086***	0.003	0.005
	(0.016)	(0.024)	(0.023)
ll-being Measures (Wave 1)			
Total Expenditure (GHS) (weekly)	315.472***	27.986	-2.251
	(22.551)	(31.742)	(30.597)
Food expenses inside home (GHS)	143.205***	-8.441	-11.013
	(8.720)	(9.144)	(11.349)
Food expenses outside home (GHS)	50.872***	7.364	4.220
	(3.723)	(7.637)	(5.286)
Utilities expenses (GHS)	22.411***	11.264	-4.517
	(6.048)	(9.177)	(6.838)
Personal care expenses (GHS)	13.085***	3.793	-1.831
	(1.618)	(3.145)	(2.135)
Education expenses (GHS)	23.779***	-4.649	1.730
	(6.459)	(7.525)	(8.814)
Health expenses (GHS)	56.477***	13.818	5.794
	(12.243)	(17.491)	(17.465)
Durables expenses (GHS)	5.643**	4.837	3.366
	(2.465)	(6.845)	(4.281)
Threatened Partner (1 = never to 4 = very often)	1.195***	0.028	-0.030
	(0.038)	(0.047)	(0.047)
Hit Partner (1 = never to 4 = very often)	1.123***	0.024	0.011
	(0.033)	(0.047)	(0.041)
log K10	2.821***	-0.006	0.001
	(0.020)	(0.024)	(0.025)
Severe Distress 0-1	0.101***	-0.025	0.010
	(0.016)	(0.020)	(0.021)
I'm tired (mentally, emotionally, or socially) of COVID-19 0-1	0.523***	0.002	0.048
	(0.026)	(0.035)	(0.038)
Corroborative Mental Health Measures (Wave 1)			
I'm depressed (1 = disagree to 5 = agree)	1.616***	-0.052	0.004
	(0.050)	(0.064)	(0.072)
I'm relaxed (1 = disagree to 5 = agree)	2.885***	-0.053	0.053
	(0.082)	(0.092)	(0.090)
I'm satisfied with life, all else equal (1 = disagree to 5 = agree)	2.533***	-0.119	0.131
	(0.081)	(0.097)	(0.088)
I'm satisfied with finances, all else equal (1 = disagree to 5 = agree)	2.072***	-0.091	0.101
	(0.064)	(0.073)	(0.084)

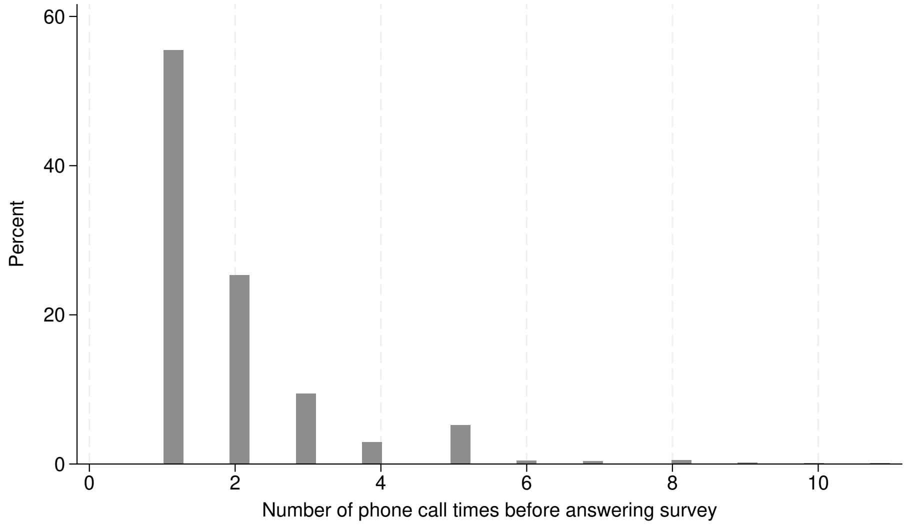
Note: Observations are at the individual level. Each row is a separate regression. Clustered standard errors (at the district level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Mean baseline characteristics are also balanced across treatment arms. **Results are similar with and without controls for randomization strata dummies.**

Table A5: **Balance test: pre-intervention treatment-control differences**

Variable	Constant	Lumpsum	Installments
Baseline Controls (Wave 1)			
Female 0-1	0.146***	0.003	0.000
	(0.018)	(0.021)	(0.023)
Akan ethnic 0-1	0.378***	-0.029	-0.015
	(0.033)	(0.030)	(0.033)
Married 0-1	0.901***	0.027	0.002
	(0.016)	(0.019)	(0.021)
Attained Junior High School (JHS) 0-1	0.789***	0.003	-0.019
	(0.021)	(0.030)	(0.027)
Household size (number)	7.239***	-0.185	-0.829***
	(0.261)	(0.339)	(0.244)
Self-employed 0-1	0.786***	-0.050*	-0.022
	(0.022)	(0.028)	(0.029)
Operates in informal sector 0-1	0.807***	-0.028	0.006
	(0.021)	(0.028)	(0.026)
Personal income (1 to 5 scale) (monthly)	1.629***	-0.016	-0.007
	(0.055)	(0.070)	(0.070)
Self does housework during pandemic 0-1	0.173***	-0.014	-0.001
	(0.019)	(0.025)	(0.027)
In previously lockdown region 0-1	0.185***	0.001	-0.007
	(0.048)	(0.009)	(0.010)
Aware of COVID-19 0-1	0.995***	0.003	0.003
	(0.004)	(0.005)	(0.005)
Trust Government's estimates about COVID-19 0-1	0.805***	-0.019	0.000
	(0.022)	(0.027)	(0.028)
Has relocated / moved in past 7days 0-1 (Wave 2)	0.012*	0.003	0.003
	(0.007)	(0.008)	(0.007)
More Baseline Controls (Wave 0)			
Poverty rate (%) (Schreiner 2005) (Wave 0)	23.226***	-1.874	-1.710
	(1.524)	(1.245)	(1.333)
Staying together with mother 0-1 (Wave 0)	0.062***	0.007	0.008
	(0.013)	(0.017)	(0.018)
Has no religion 0-1 (Wave 0)	0.052***	0.006	-0.001
	(0.011)	(0.014)	(0.016)
Staying together with spouse 0-1 (Wave 0)	0.888***	-0.040*	-0.018
	(0.015)	(0.023)	(0.022)
Age at marriage (Years) (Wave 0)	24.680***	0.208	0.558
	(0.262)	(0.390)	(0.391)

Note: Observations are at the individual level. Each row is a separate regression. The F and Chi-squared tests are conducted using the pooled indicator **1(Communication Credit)** as the outcome and excluding all the communication and well-being outcomes. Clustered standard errors (at the district level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Mean baseline characteristics are also balanced across treatment arms. **Results are similar with and without controls for randomization strata dummies.**

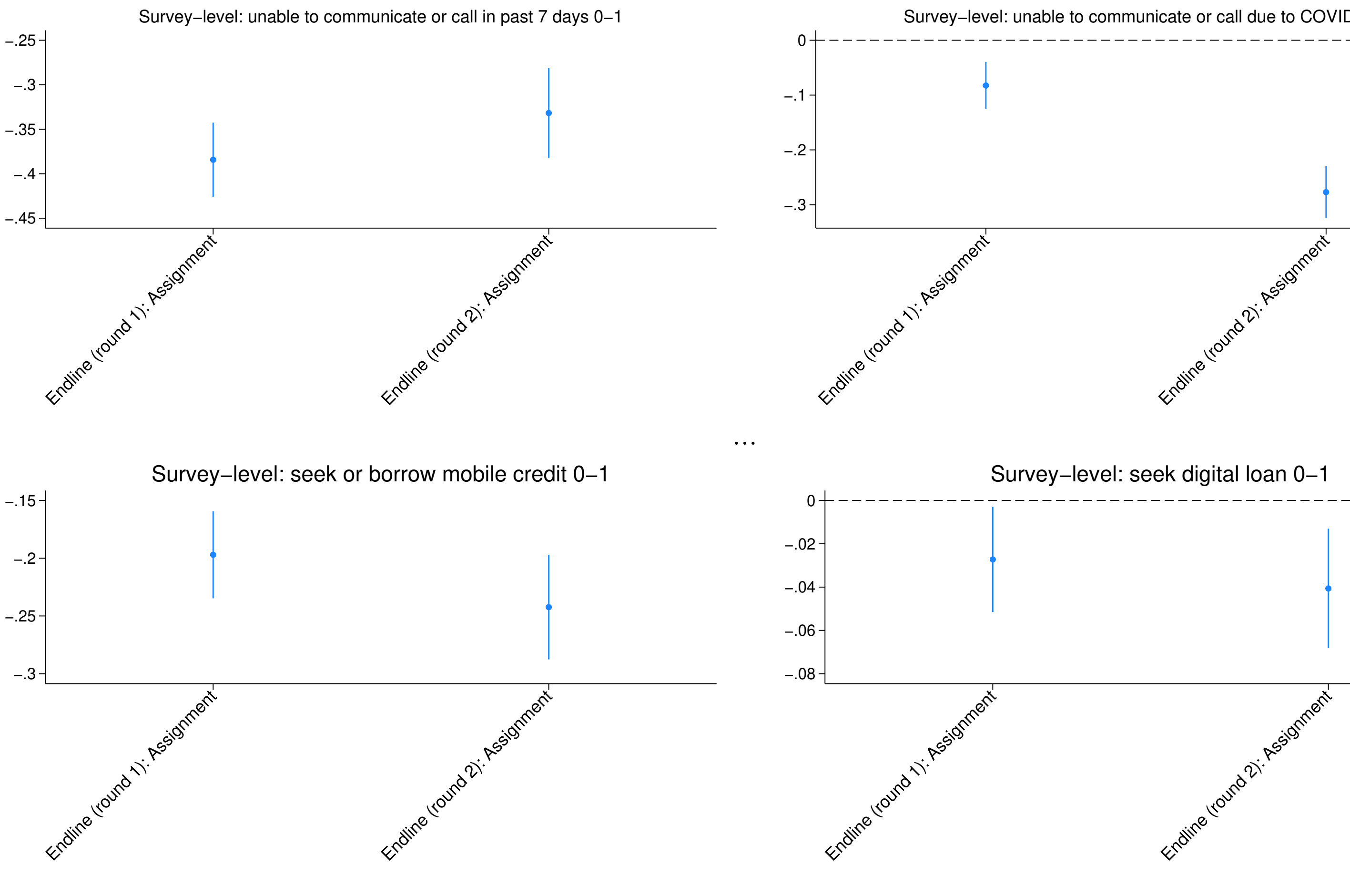
Figure A5: **Phone calls and reachability of individuals**



VI.6 Further Results – Tables and Figures

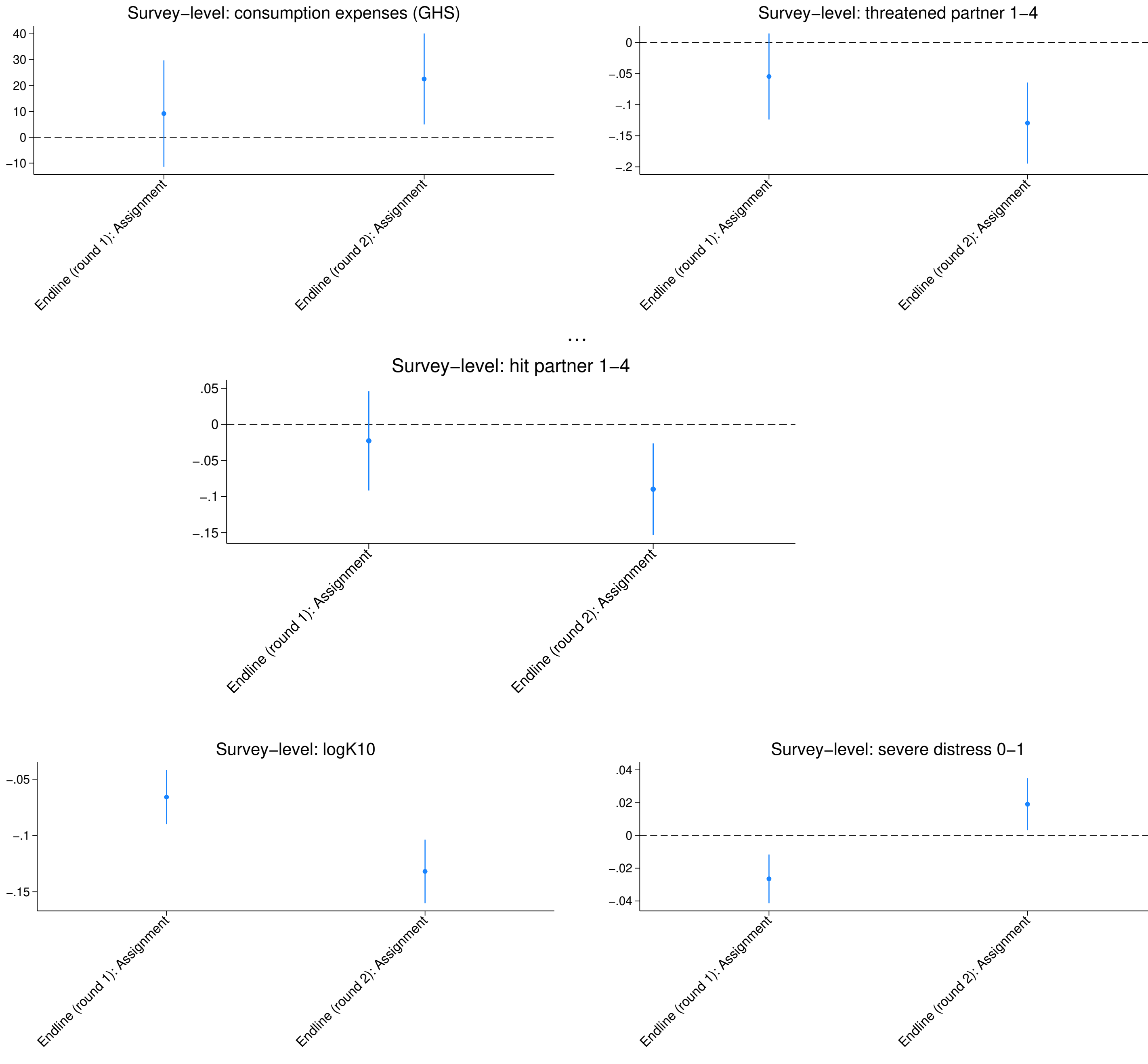
POOLED EFFECTS OVER TRAJECTORY

Figure A6: MITIGATION OF COMMUNICATION CONSTRAINTS



Note: Estimates are from a model that includes randomization strata (district) fixed effects, survey date fixed effects, and double-post LASSO specification which considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject × date level. Standard errors are clustered at the individual level (the level of treatment). 90% confidence intervals are displayed around the estimates. Table of coefficients and standard errors available upon request.

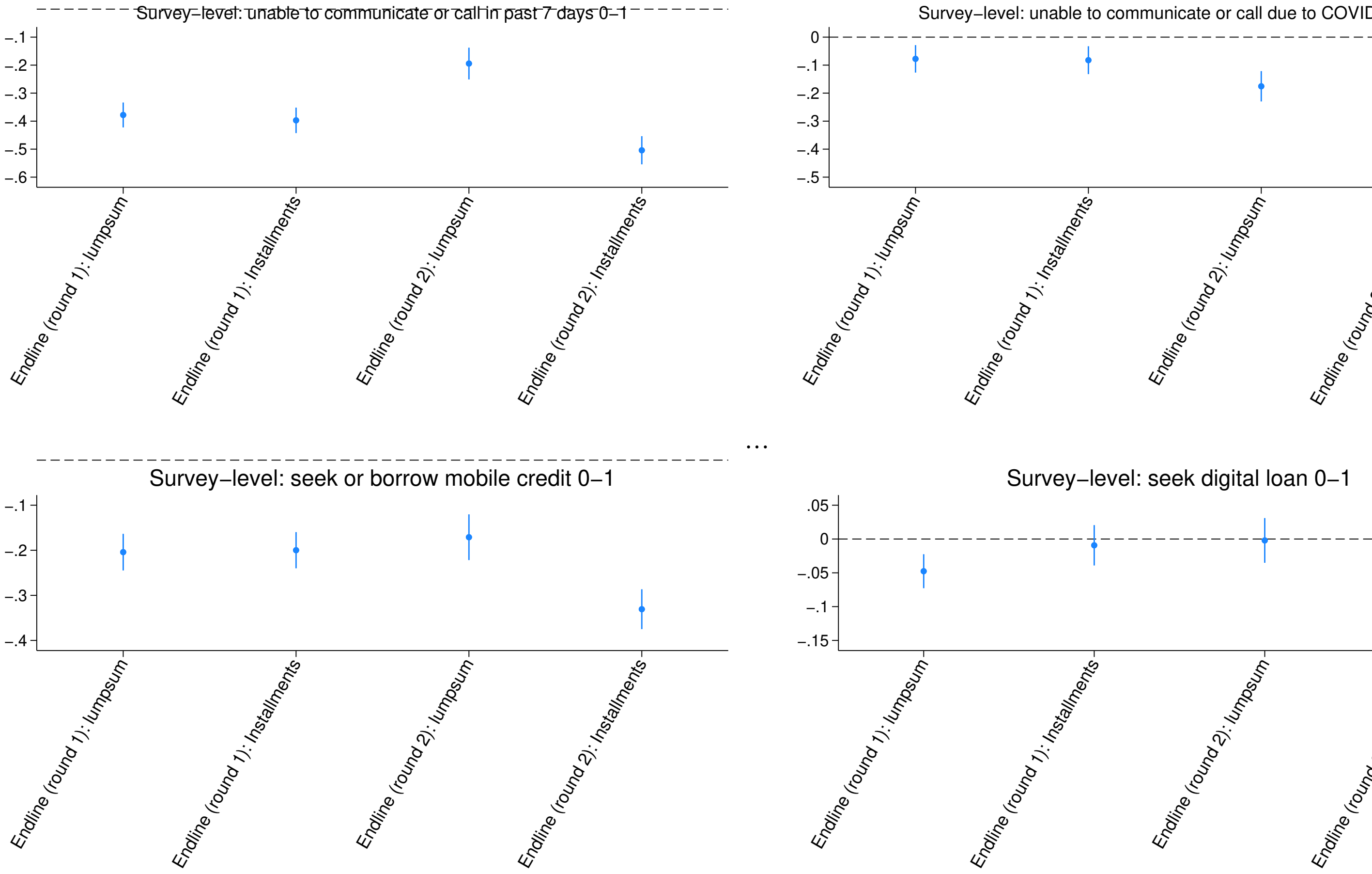
Figure A7: **IMPACTS OF COMMUNICATION PROGRAMS ON WELL-BEING MEASURES**



Note: Estimates are from a model that includes randomization strata (district) fixed effects, survey date fixed effects, and double-post LASSO specification which considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Standard errors are clustered at the individual level (the level of treatment). 90% confidence intervals are displayed around the estimates. Table of coefficients and standard errors available upon request.

SEPARATE EFFECTS OVER TRAJECTORY

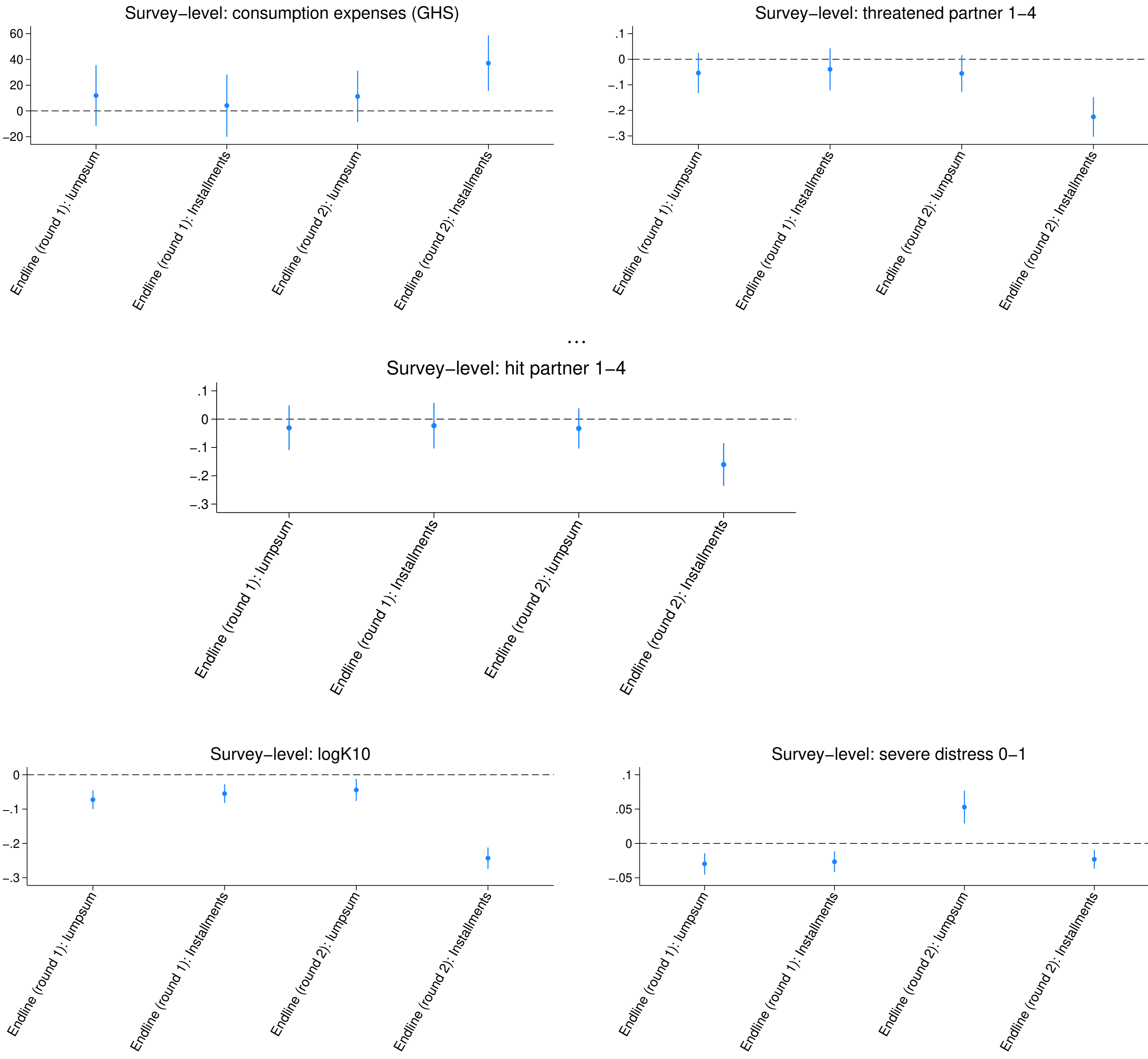
Figure A8: **MITIGATION OF COMMUNICATION CONSTRAINTS**



…

Note: Estimates are from a model that includes randomization strata (district) fixed effects, survey date fixed effects, and double-post LASSO specification which considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject × date level. Standard errors are clustered at the individual level (the level of treatment). 90% confidence intervals are displayed around the estimates. Table of coefficients and standard errors available upon request.

Figure A9: **IMPACTS OF COMMUNICATION PROGRAMS ON WELL-BEING**



Note: Estimates are from a model that includes randomization strata (district) fixed effects, survey date fixed effects, and double-post LASSO specification which considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Standard errors are clustered at the individual level (the level of treatment). 90% confidence intervals are displayed around the estimates. Table of coefficients and standard errors available upon request.

HETEROGENEOUS EFFECTS

Table A6: **Impacts of communication programs on well-being by poverty**

VARIABLES	(1) Total (GHS) Expenditure	(2) Threatened Partner 1-4	(3) Hit Partner 1-4	(4) log K10	(5) Severe Distress 0-1
Communication Credit (β)	19.13	0.0231	0.00938	-0.0798***	0.00103
	(16.31)	(0.0480)	(0.0487)	(0.0201)	(0.00974)
Poverty Likelihood	-0.732*	0.00232	0.000609	0.000473	-0.000518
	(0.394)	(0.00184)	(0.00184)	(0.000564)	(0.000327)
Credit x Poverty	-0.307	-0.00436**	-0.00229	-0.000714	-0.000215
	(0.477)	(0.00208)	(0.00202)	(0.000636)	(0.000362)
Observations	2,018	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	219.573	1.247	1.166	2.704	0.025
p-value: Romano-Wolf Correction treatment	0.950	0.950	0.950	0.010	0.950
p-value: Romano-Wolf Correction poverty	0.010	0.010	0.040	0.010	0.743
p-value: Romano-Wolf Correction interaction	0.941	0.158	0.663	0.842	0.832

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported separately for consumption expense outcomes family (Total (GHS) Expenditure; Food-In (GHS); Food-Out (GHS); Utilities (GHS); Personal care (GHS); Educ. (GHS); Health (GHS); Durables (GHS)), and for mental health and domestic violence outcomes family (Threatened Partner 1-4; Hit Partner 1-4; log K10; Severe Distress 0-1). NE denotes not estimable.

Table A7: **Impacts of communication programs on well-being by informality**

VARIABLES	(1) Total (GHS) Expenditure	(2) Threatened Partner 1-4	(3) Hit Partner 1-4	(4) log K10	(5) Severe Distress 0-1
Communication Credit (β)	-25.07	-0.0728	-0.0990	-0.00704	0.0300**
	(26.17)	(0.0680)	(0.0669)	(0.0317)	(0.0120)
Informal Sector 0-1	-54.64**	0.126*	0.0696	0.0961***	0.0526***
	(25.93)	(0.0731)	(0.0682)	(0.0317)	(0.0149)
Credit x Informal 0-1	44.94	-0.00107	0.0648	-0.107***	-0.0418***
	(28.63)	(0.0818)	(0.0799)	(0.0347)	(0.0148)
Observations	2,018	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	219.573	1.247	1.166	2.704	0.025
p-value: Romano-Wolf Correction treatment	0.921	0.475	0.535	0.178	0.416
p-value: Romano-Wolf Correction informal	0.030	0.277	0.426	0.020	0.050
p-value: Romano-Wolf Correction interaction	0.871	0.871	0.842	0.139	0.248

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). NE denotes not estimable, which occurs due to insufficient sample from individuals in the informal sector with severe mental distress experiences. Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported separately for consumption expense outcomes family (Total (GHS) Expenditure; Food-In (GHS); Food-Out (GHS); Utilities (GHS); Personal care (GHS); Educ. (GHS); Health (GHS); Durables (GHS)), and for mental health and domestic violence outcomes family (Threatened Partner 1-4; Hit Partner 1-4; log K10; Severe Distress 0-1).

Table A8: **Impacts of communication programs on well-being by gender**

VARIABLES	(1) Total (GHS) Expenditure	(2) Threatened Partner 1-4	(3) Hit Partner 1-4	(4) log K10	(5) Severe Distress 0-1
Communication Credit (β)	11.63	-0.0880**	-0.0631*	-0.0885***	-0.00195
	(11.04)	(0.0360)	(0.0351)	(0.0139)	(0.00725)
Female 0-1	1.490	-0.0625	-0.142*	0.0214	0.00286
	(23.09)	(0.0776)	(0.0751)	(0.0344)	(0.0182)
Credit x Female 0-1	9.426	0.0622	0.132	-0.0634	-0.0126
	(27.50)	(0.0939)	(0.0917)	(0.0405)	(0.0225)
Observations	2,018	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	219.573	1.247	1.166	2.704	0.025
p-value: Romano-Wolf Correction treatment	0.782	0.218	0.782	0.010	0.782
p-value: Romano-Wolf Correction female	0.901	0.901	0.901	0.287	0.901
p-value: Romano-Wolf Correction interaction	0.970	0.970	0.970	0.149	0.970

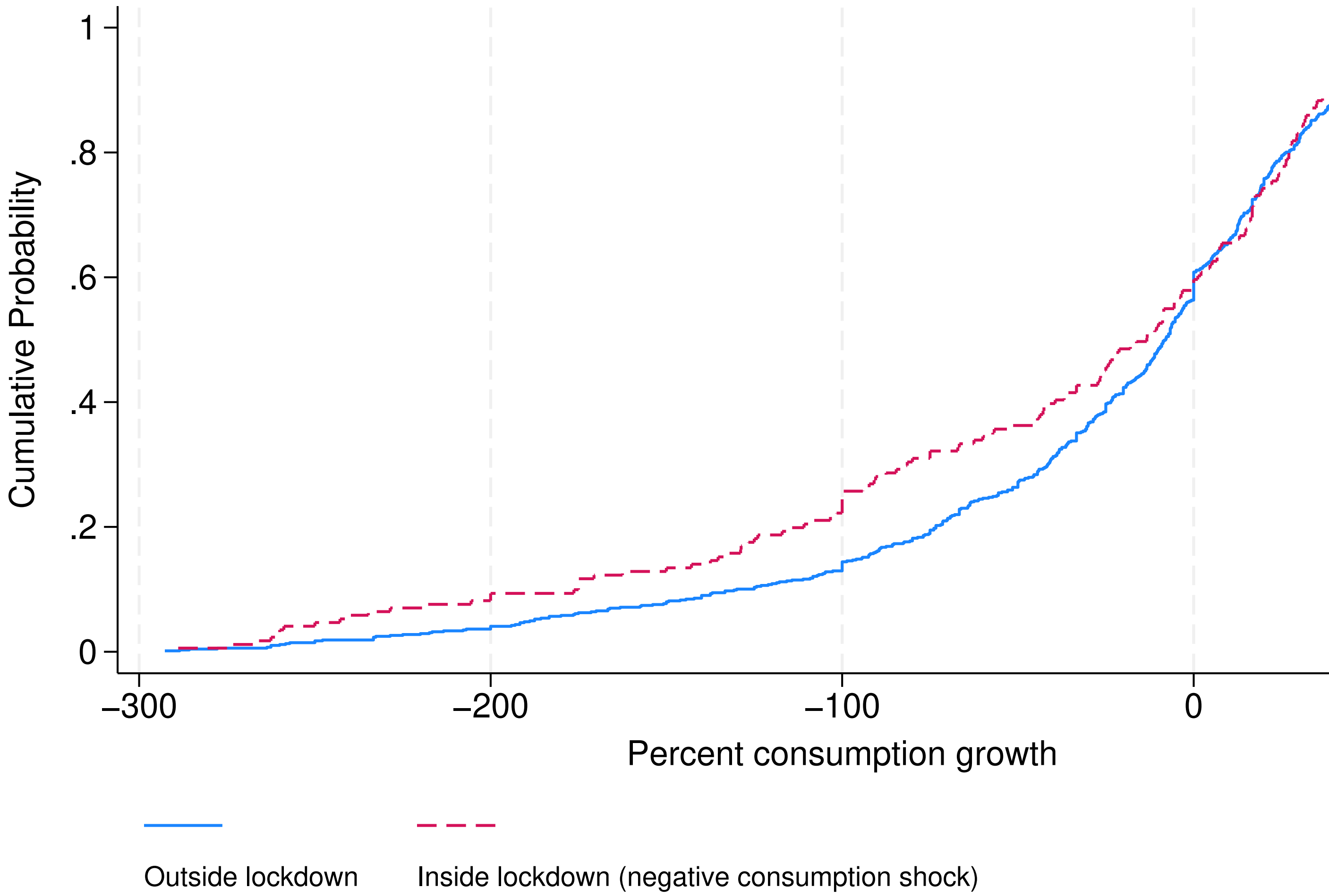
Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** p<0.01 (1% level), ** p<0.05 (5% level), * p<0.1 (10% level). Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported separately for consumption expense outcomes family (Total (GHS) Expenditure; Food-In (GHS); Food-Out (GHS); Utilities (GHS); Personal care (GHS); Educ. (GHS); Health (GHS); Durables (GHS)), and for mental health and domestic violence outcomes family (Threatened Partner 1-4; Hit Partner 1-4; log K10; Severe Distress 0-1).

Table A9: **Impacts of communication programs on well-being by locked-down**

VARIABLES	(1) Total (GHS) Expenditure	(2) Threatened Partner 1-4	(3) Hit Partner 1-4	(4) log K10	(5) Severe Distress 0-1
Communication Credit (β)	0.485	-0.0856**	-0.0501	-0.0908***	-0.00680
	(11.05)	(0.0386)	(0.0377)	(0.0141)	(0.00729)
Locked-Down 0-1	157.2***	-0.0607*	-0.0359	0.106***	0.00139
	(55.82)	(0.0341)	(0.0321)	(0.0391)	(0.00672)
Credit x Locked-down 0-1	64.45**	0.0406	0.0299	-0.0300	0.0150
	(25.07)	(0.0658)	(0.0661)	(0.0333)	(0.0185)
Observations	2,018	2,018	2,018	2,018	2,018
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	PD LASSO	PD LASSO	PD LASSO	PD LASSO	PD LASSO
Mean of dep. variable	219.573	1.247	1.166	2.704	0.025
p-value: Romano-Wolf Correction treatment	0.901	0.188	0.901	0.010	0.901
p-value: Romano-Wolf Correction locked	0.050	0.040	0.426	0.426	0.693
p-value: Romano-Wolf Correction interaction	0.178	0.980	0.980	0.980	0.980

Note: District is the randomization strata. The double-post LASSO specification considers all individual controls, and individual district and survey date fixed effects in the possible control set. Controls include: individual's age, 0-1 indicator for whether married or not, 0-1 indicator for whether belongs to akan ethnic group or not, 0-1 indicator for whether self employed or not, household size, 0-1 indicator for whether operates in the informal sector, monthly personal income over an ordinal scale of 1 to 5, 0-1 indicator for whether attained junior high school (JHS) education, and individual's gender. Observations are at the subject $\times$ date level. Clustered standard errors (at the individual level; the level of treatment) are reported in parentheses. *** $p<0.01$ (1% level), ** $p<0.05$ (5% level), * $p<0.1$ (10% level). Romano-Wolf multiple hypothesis correction p-values (Romano and Wolf [2005]) reported separately for consumption expense outcomes family (Total (GHS) Expenditure; Food-In (GHS); Food-Out (GHS); Utilities (GHS); Personal care (GHS); Educ. (GHS); Health (GHS); Durables (GHS)), and for mental health and domestic violence outcomes family (Threatened Partner 1-4; Hit Partner 1-4; log K10; Severe Distress 0-1). NE denotes not estimable.

Figure A10: **Distribution of consumption growth among individuals inside and outside pandemic's lockdown areas**



Note: Figure plots the distribution (CDF) of consumption growth per week at endline for the different subsamples (lockdown areas vs non-lockdown areas). Observations are at the individual level. Median (mean) percent consumption growth is -13% (-45%) for individuals in lockdown areas and -8% (-27%) for those in non-lockdown areas. From a Kolmogorov–Smirnov (KS) test for the equality of distributions, p-value equals 0.020 (for equality test, we trimmed the individual consumption growth outcome at the 5% level). Equality tests reject the null that the distributional pairs are equal.

VI.7 Definition of Relevant Select Variables – Questions

Communication constraints (un)mitigation:

Consider the last 7 days:

1. Unable to call in past 7days 0-1: `Were you confronted with the need to call others (i.e., family, friends or work) but unable to call because you/ household lacked enough communication resources to cover costs? 0=No, 1=Yes`
2. Borrow airtime 0-1: `Have borrowed airtime due to unexpected circumstances to make calls? 0=No, 1=Yes`
3. Seek digital loan 0-1: `Have taken a digital loan due to unexpected circumstances to make calls? 0=No, 1=Yes`
4. Unable to call due to COVID19 0-1: `Are you sometimes unable to see or communicate with your family and friends due to COVID19, its lockdown restrictions and other personal avoidance steps you have taken? 0=No, 1=Yes`

Gender and Domestic violence relations:

Consider last 7 days: Please indicate how often you act to the following:

USE CODES:

`1=Never (less than 1 time in 7 days), 2=Sometime (1-2 times in 7 days), 3=Often (3-4 times in 7 days), 4=Very often (5-7 times in 7 days), 5=No Answer (if you want/feel uncomfortable to say)`

1. Threatened Partner 1-4: `How often do you threaten to hurt your partner or someone close to your partner?`
2. Hit Partner 1-4: `How often do you hit or throw something at your partner?`

Mental Health (K10):

Consider last 7 days: Please indicate how often you feel about the following:

USE CODES:

1=None of the time (less than 1 time in 7 days), 2=A little of the time (1-2 times in 7 days), 3=Some of the time (3-4 times in 7 days) 4=Most of the time (5-6 times in 7 days), 5=All of the time (7 times in 7 days)

1. About how often did you feel tired out for no good reason?
2. About how often did you feel nervous?
3. About how often did you feel nervous that nothing could calm you down?
4. About how often did you feel hopeless?
5. About how often did you feel restless or fidgety?
6. About how often did you feel so restless you could not sit still?
7. About how often did you feel depressed?
8. About how often did you feel that everything was an effort?
9. About how often did you feel so sad that nothing could cheer you up?
10. About how often did you feel worthless?

Consumption Expenditures (weekly):

1. What is the total value (in GHS) of all food and beverage items your household (i) purchased and consumed, (ii) consumed from your own stock or production, or (iii) received as a gift and consumed over the last 7 days? NOTE: Please only include food and beverage items consumed in the 7 days ...GHS
2. What is the total value (in GHS) of all food and beverage items you or any member of your household purchased and consumed from outside the house over the last 7 days? NOTE: This includes items purchased outside the house in

restaurants, cafeterias, canteens/kiosks, as well as products such as spirits, tobacco, stimulants, etc. ...GHS

3. What is the total value (in GHS) of house rents, house repair costs and utilities that were paid for, purchased, or acquired from other sources (ie gifts and in-kind) by your household over the last 7 days? NOTE: Utilities include sewerage, electricity, water, gas, cooking fuels, house servants, etc. ...GHS

4. What is the total value (in GHS) of products and services for personal use and care, that were paid for, purchased, or acquired from other sources (ie gifts and in-kind) over the last 7 days by your household? NOTE: Personal care products and services include barber services, electrical appliances for personal care, oils, soaps, etc. Personal use products and services include jewelry, accessories (watches, clocks, clothing, etc.), cultural services, mobile airtime services, financial service fees, transportation costs. ...GHS

5. What is the total value (in GHS) of education expenses (i.e., all tuition or fees including all educational scholarships) over the last 7 days by your household? ...GHS

6. What is the total value (in GHS) of consultation or treatment services, and pharmaceutical or therapeutic products purchased last 7 days by your household? ...GHS

7. What is the total value (in GHS) of durable products such as furniture, electronics and other household appliances, purchased over the last 7 days by your household? NOTE: This includes furniture, household appliances (large and small), repair of household appliances, miscellaneous accessories such as TVs, laptops, cars, mobile phones, bicycles, torches, batteries, solar lamps, etc. ...GHS

8. Total expenditure: add 1 to 8 ...GHS

VI.8 Marginal Value of Public Funds (MVPF)

We use our causal estimates to compute the MVPF (Hendren and Sprung-Keyser 2020) for a policy that provides communication credit to low-income adults for two months. The MVPF is a ratio of society's willingness to pay (private benefit) for this policy to the net cost of the policy to the government (here, an "imagined" funder).

VI.8.1 Society's Willingness to Pay (MVPF numerator)

We estimate this to include two main components.

First, is the averted (otherwise) social cost of mental health burden, ξ. Mental health disorders account for 13% of the overall global disease burden (Collins et al. [2011]), which is likely higher in low-income countries (Adhvaryu et al. [2019]); we assume 13%. Health expenditure per capita in Ghana is US$78 (World Bank [2018]). With a treatment effect of -10% reduced mental destress rate (or -25% for severe mental distress; we assume -10%), we conservatively estimate the averted social cost of mental health burden to be 0.10x0.13xUS$78=+US$1.014. This ξ estimate is very conservative: Addo et al. [2013] estimate that the average monthly household cost of mental healthcare in Ghana is US$60.24 (i.e., 2xUS$60.24=US$120.48 for two months), so with a treatment effect of -10% reduced mental destress rate and a national average household size of 4.5 people per household, this will imply 0.1xUS$120.48/4.5=+US$2.68 averted social cost, which is 2.6 times larger. Second, is the individual beneficiary's willingness to pay for not visiting the hospital or not getting mentally unwell, η. This includes three sub-components: (i) out-of-pocket health bill η_1 (0.10x0.13xUS$63=+US$0.82; out-of-pocket health expense is US$63 [World Bank 2018]); (ii) travel cost to health centers η_2 (assumed to be 20% of the estimated out-of-pocket health bill = 0.2xUS$0.82=+US$0.203; Addo et al. [2013] suggest using 74% for such indirect costs but we assume 20%); and (iii) lost income from missed work η_3 (assumed to be only 5% of the average earnings of non-farm enterprises = 0.05xUS$231=+US$11.55 for two months; most individuals in our sample [around 80%] operate informal non-farm enterprises and the total average annual earnings of non-farm enterprises is US$1,385 in 2021 US$ [Ghana Statistical Service, GLSS 7 Table 9.6]; the treatment effects were all concentrated on individuals operating informal enterprises, see Table A7).[10]

Combining all the components, the MVPF's numerator = $\xi + \sum_{i=1}^{3} \eta_i$=US$13.590 for the average treated individual.[11].

VI.8.2 Net Cost to the "imagined" Funder / Government (MVPF denominator)

We estimate this to include two main components.

First, is the cost of providing communication transfer for two months, G (+US$7.0). Second, is the missed communication services tax (CST) revenue if individuals do not communicate or stay connected, μ. In Ghana, the CST is used to finance the National Youth Employment Programme (NYEP) (≥20% of the CST) and support other national development activities. Using the prevailing 5% CST rate (Ghana Revenue Authority [2020]), we estimate that the government loses 0.05xUS$7.0= -US$0.35. In computing the net cost to the government of this policy, it is important to note that (i) communication is a network good so the ultimate economic incidence of these communication transfers extends to other individuals: others might benefit from receiving mobile phone calls from the treated individual (positive externalities) but this might also create congestion hassle or traffic on the communication network (negative externalities). We assume (i) and (ii) to be equal. If the positive externalities dominate, as we would expect (see Björkegren [2019] for an example

[10] Informal non-farm business income may either be consumed in the household (where we find no impacts) or invested (where our impacts are concentrated given that our treatment effects were all concentrated on individuals operating informal enterprises).

[11] We drop the direct value of the communication subsidy to beneficiaries (+US$7.0) to avoid double counting. In standard maximization models, the willingness to pay would have just been the size of the subsidy *if* people are fully optimizing. Here, it is reasonable to assume that people are not fully optimizing (see e.g., our evidence that the installment program has larger and more sustainable effects compared to the lumpsum, with the exception of consumption, which may reflect either time inconsistency or social pressure problems from receiving one-time large transfers). Given this potential mis-optimization (the envelope theorem does not easily apply and so the benefits the subsidy delivers to people are not already captured by the subsidy), the willingness to pay includes the benefits on mental health and its associated cost reductions (ξ and η).

in Rwanda), then the total cost of this policy is over-estimated in this dimension. Further, we conservatively did not factor in the reduced fiscal cost from less hospital visits generally due to the reduced likelihood of mental health disorders.

Lastly, combining all the components, the MVPF's denominator = $G+\mu$=US\$6.65 for the average treated individual.

VI.8.3 MVPF Estimate

Taking the ratio, we estimate a conservative MVPF of providing communication credit to be $\frac{13.590}{6.650} = 2.044$. Notice that in determining the MVPF, we intentionally bias the estimates to understate the benefits and overstate the costs. With a current total population of about 31,732,129 in Ghana, an adult population of 18,073,230 (57% of the total population), and the poverty rate of our study's sample of adults being 22%, the policy's total benefit will be US$54,035,343 (=0.22x18,073,230xUS$13.590) against a total cost of US$26,441,135 (=0.22x18,073,230xUS$6.650).