The Big Five personality traits and borrowers behavior: evidence from group-based lending in Gambia

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Abstract

In this study, we look at non-cognitive traits and see whether they matter for repayment behavior of borrowers in joint liability schemes. To measure non-cognitive traits, we use a big five inventory consisting of 33 items. These items are then grouped into five main sub-groups. A borrower rate herself on each of the items and the average score of a borrower in each element of the subgroups is determined and this is related to the probability of the borrower to default and consequently the probability of the group to default. Using data from an NGO based microcredit program in Gambia, we find that personality trait variables such as Extraversion, Agreeableness, Neuroticism, and Openness to Experience matters for the likelihood of default. In particular, an increase in the amount of these traits is associated with lower probability of default. Hence, our results show that adverse selection problems exist in microcredit markets and should not be ignored. Consequently, screening tools that reveal such information could help enhance the performance of microcredit programs.

Keywords: Non-cognitive traits; Groups; repayment behavior; Gambia

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1 Introduction

Among the various tools that have been suggested for dealing with poverty, one that has received significant attention over the years, especially in developing countries, is the issue of financial inclusion, in particular the access of credit services by the poor. Access to credit is important because majority of the extreme poor in developing countries are dwellers of rural communities. In these places, there exists very few conventional money lending institutions. The absence of conventional means of credit in areas that are predominantly inhabited by the poor is due to fact that poor borrowers do not have sufficient collateral to back their loans. Meanwhile, without access to credit low-income households will not have access to capital required to finance projects that can get them out of poverty. It is for this reason that the provision of credit to the poor via non-conventional means (such as microcredit) have been heralded as an important tool to boost global efforts to combat poverty and underdevelopment. Such a notion became strongly favored following the successes of Mohammed Yunus and the Grameen Bank in Bangladesh. [1]

The central idea in microcredit (often called micro-lending) is the provision of credit, in the form of small loans, to low-income earners (mostly the extreme poor in rural areas). This is paramount because when people have access to credit they can use their loans to better their economic status and create employment opportunities for themselves in a way that enables them to have stable income paths, even in the advent of unexpected shocks. Access to credit by the poor from formal money lending institutions (such as commercial banks) is limited because of the stringent conditions of the latter that are due to the high risk associated with lending to the former. Furthermore, traditional means of credit creation in rural areas are associated with very high interest rate, which makes it difficult for the poor to borrow money and make ends meet. It is for this reason that micro-lending is viewed as an excellent tool for dealing with the problem of financial inclusion, especially in developing countries.

From the different variants of micro-credit, one that has received significant attention is a group and joint liability lending. It has captured the attention of economist as one of the most promising means to get credit to those without access to formal credit, (Wydick, 1999). In such schemes, loans are given to a group and all members of the group are responsible for the repayment of the loan; that is all individuals in a group are jointly liable for a loan. Such a lending program is ideal because it solves a fundamental problem in providing credit to borrowers in credit markets (when there are information asymmetries) – the bottleneck of distinguishing between high-risk and low-risk borrowers. In addition, it also minimizes the fixed

[1] As of 2011 the Grameen Bank was providing credit to about 8.3 million people, 97% of who are women, (Grameen, 2016).

cost associated with small loans, (Karlan, 2005). The difficulty associated with screening poor borrowers plus lack of collateral increases the cost of lending to the poor (Aghion and Gollier, 2000). Group lending increase loan repayments because joint liability leads to lower interest rate. This brings back low-risk borrowers into the credit market, which increases repayments. Hence, group lending enhances loan repayments because joint liability motivates individual members of a group to engage in activities like screening (Varian, 1990; Ghatak, 1999) and monitoring and enforcement (Stiglitz, 1990; Besley and Coate, 1995) that minimize the incentive to default. Consequently, most of the empirical evidence on group lending and loan repayment or delinquency (e.g Wydick, 1999; Hermes et al., 2005; Karlan, 2007; Cassar et al., 2007; Ahlin and Townsend, 2007) focuses on the impact of factors, such as social capital, that affect these mechanisms on the performance of the schemes. This is done while controlling for individual cognitive traits such as income, age, education, among others on the behavior of borrowers in such programs.

However, there has not been much focus on the relevance of non-cognitive traits on borrowers repayment behavior. From a broader sense, such a challenge is not limited to only the study of micro-lending but economics as a whole. In economics, most of the attempts to characterize individual differences in socioeconomic outcomes have been centered on cognitive traits, (Borghans et al., 2008). (Almlund et al., 2011) argued that there exist significant imbalance in highlighting how cognitive skills might relate to other non-cognitive traits. This is quite intriguing given that there exist significant evidence in personality psychology that personality traits do affect life outcomes.[2] The limited evidence that is available in main stream economics is concentrated on the impact of personality trait on labor market outcomes. Recently, however, there has been an increase in the number of studies that analyses how the behavior of economic actors can be related to non-cognitive traits. But few studies have looked at the effect of traits on behavior in other markets like credit markets.

It is against this backdrop that we embark on this study as an attempt to contribute to the evidence of the impact of non-cognitive traits on the behavior of economic actors; in this case, borrowers in credit markets. In particular, we use the dispositional aspects of a borrower's behavior to study the performance of a grouped based microcredit programs in Gambia that targets only women.[3] The psychological traits are measured using the five-factor model (FFM in short), which is the main instrument used for studies on personality traits. We study whether these traits are related to the borrowers repayment behavior. Repayment behavior is measured

[2](see Ozer and Benet-Martinez, 2006, for details.)

[3]Lot of evidence have shown that when it comes to poverty in developing countries women tends to share a large chunk of the burden. Thus, program that target women are likely to have more positive impacts on households.

through a question in our survey that asks the borrower whether she has ones defaulted on a loan. Our study is related to a study by (Karlan et al., 2012), from here KMR. However, our paper differs from these authors in that we used a longer BFI inventory than KMR. In measuring traits, the use of large instruments is encourage because they have a higher Psychometric validity than short instruments.

In a broader sense, our study will be an addition to the scanty evidence of the impacts of psychological traits on economic behavior. This of particular importance to financial institutions especially those that lend to poor borrowers who, among other limitation, do not have credit histories that could be used to gauge their qualification for credit. Thus, screening based on traits could be useful substitutes for credit history and other formal requirements that poor borrowers cannot fulfill. Hence, this is a good to implore in checking whether a borrower can repay her loan or not.

Our paper is structured into five sections. Following the introduction, the next section discusses the evidence in the literature. In section three, we describe our data collection and sampling technique. In section 4 we report and discuss the results. Finally, in the last section, we summarize our main findings and give a conclusion.

2 Literature Review

The study of Personality trait is as old as the study of the human language, (Matthews et al., 2003). According to (Almlund et al., 2011), Personality is a system of relationships that map traits and other determinants of behavior into actions. Hence, personality trait is one of the determinants of personality. (Costa Jr and McCrae, 1995) define personality trait as "the relatively enduring styles of thinking, feeling, and acting that characterize an individual". For this reason, it is widely believed, by personality psychologist and other social scientist, that there exist a relationship between personality traits and a lot of life outcomes such as schooling, employment, and career paths,(Matthews et al., 2003).

Despite well-developed evidence in psychology that non-cognitive traits such as personality affect behavior, the empirical evidence on the impact of non-cognitive traits on economic behavior is still limited. Many of the studies in economics on the subject are focused on the impact of personality traits on labor market outcomes and the relationship between personality traits and trusting behavior or trustworthiness in behavioral games.

In studying the impact of personality trait on household finances in Britain, (Brown and Taylor, 2014) found that personality traits relating to factors in the Big Factor Model (such as extraversion and openness to experience) are highly correlated with personal finances.

There is also an extensive (but not in any way exhaustive) strand of literature that is focused on the relationship between personality traits and behavior using the game theory perspective. For instance, (Boone et al., 1999) study (non)-cooperative behavior in prisoner's dilemma games and the impact of personality traits on the outcomes of the games. They found evidence that personality traits such as internal locus of control, high self monitoring and high sensation seeking are related to cooperative behavior. In a similar vein, (Kugler et al., 2014) study whether personality traits (such as anxiousness and aggressiveness that are facets of the neuroticism) affect strategic behavior. They use a two player entry level game in which a player gets a guaranteed reward by opting to stay out, gains more when the player is the only one that enters, and gain less when both decide to enter. They found that a player's choice to enter or stay out in the game is determined by her level of anxiousness and aggressiveness. In particular, anxious players enter less and aggressive players enter more. In addition, they found that anxious players were less likely to enter than non-anxious players and aggressive players were more likely to enter than non-aggressive players.

(Hammond and Morrill, 2016) study the impact of personality on bidding behavior in English auctions with competitive sellers. They found evidence that personality traits measured using the big five taxonomy have a significant impact on bidding behavior for women.

(Braakmann, 1999) use data from the 2005 wave of the German Socio-Economic Panel survey (SOEP) to study the relationship between non-cognitive traits and the difference in labor market outcomes between men and women. He found evidence that "psychological traits" have a significant and non-negligible effect on the gender gap in employment and wages.

(Rustichini et al., 2016) used laboratory experiments to study the relationship between personality traits and economic preferences. As in similar studies, they obtained evidence that there exist a link between personality traits, particularly elements of the big five domains, and economic preferences. Their results suggest that intelligence and Neuroticism constitute the core link through which personality trait relate to economic preferences. In particular, they found that intelligence is positively correlated with patience and Neuroticism is negatively correlated with the attitude towards risk. Furthermore, they found evidence that Extraversion is related to aversion to ambiguity and Agreeableness play a significant role in both cognitive and behavioral responses in their experiments. The precise evidence they found with regards to Agreeableness was that it accurately predicts players beliefs on the action of others, with higher Agreeableness scores being associated with an inclination to expect more cooperative actors. On the basis of their evidence, they concluded that adding non-cognitive measures to many cognitive measures used by economists significantly increases the predictive power of most dependable variables, especially when these are real world economic outcomes.

In the microcredit literature, KMR was the only article we found where the relationship between personality traits and default behavior was studied. Using field experiments, they found that both individual morality and naivety have significant negative impact on default behavior. In addition, they also studied whether generalized measures of personality trait can predict default behavior and they found that these variables do not predict default. Furthermore, they argued that their evidence shows the presence of moral hazard problems in micro-lending markets and also the tendency for there to be adverse selection problems since personality traits are not observable to the lender.

3 Data and sampling

Our data comes from a survey of borrowers in the group-based lending scheme of an NGO microcredit provider in Gambia called GAWFA (Gambia Women Finance Association).[4] GAWFA is among series of NGOs run microcredit programs established in Gambia to fill the gap created by commercial banks in the access to finance.[5] The NGO is founded in 1987 by the coming together of different women groups with the vision of tackling the financial difficulties faced by women in the access to finance. However, it was not until 1997 when it got its license from the Central Bank of The Gambia, the official regulator of microfinance or microcredit institutions in Gambia, to operate as the first micro-credit institution in Gambia that is designed primarily for rural women. Thus, about 96% of their clients are women and 90% of them are dwellers of rural communities. Currently, GAWFA is providing financial access to about 14,377 women in 78 communities across the length and breadth of Gambia. As of 2015, its total loan outstanding stood at about GMD 7 million (about $200,000), making it one of the giant microcredit providers in Gambia. GAWFA offers two forms of group-based lending; which they call Large Group (LG) loan and Solidarity Group (SG) loan. The LG loans are given to groups of at least 12 members who use the loan for either the income generation activities of the group or to finance individual member's income generating activities. The SG loans, on the other hand, are disbursed to groups of 3-11 members. Most members of the SG loan groups are market vendors or family holders and the loans are used for their individual income-generating activities. GAWFA does not directly influence the formation of groups by potential borrowers; a client makes this decision individually.[6] In addition, members of a loan group act as guarantors to each other, which make all

[4] In the Gambia, lending programs targeting groups are organized through kafos or compins. These are "homogeneous group of individuals in a village with common interest", (Ouattara et al., 1993).

[5] The introductory section of (Ouattara et al., 1993) contains detail discussion of this phenomena

[6] This is could be a source for possible selection bias.

of them liable for any defaulted loan. Consequently, a loan is not considered repaid unless all the members responsible for the loan repays on time. Considering that the main argument in favor of group-based lending in the microfinance literature is that it reduces asymmetric information problems through joint liability lending, the joint liability nature of the lending schemes makes them ideal for our study.

For the sampling, we implored a multi-stage design. At the first stage, we grouped the intervention communities with one of the aforementioned schemes (LG loan or SG loan) into 4 strata given by region. In each region or strata, we randomly selected 3 to 7 intervention communities.[7] In the second stage, we randomly selected 1 to 3 groups in each intervention community and all the members of the selected groups are interviewed. If the enumerator is unable to interview any member of a selected group, then, he has to organise for a recall and the time frame for the recall is 1-7 days. If after 7 days the individual is still not available for an interview, she is considered a nonresponse.

For the respondents selected, interviews were carried out face to face using structured questionnaires. Three different set of questionnaires were administered during the survey. The first questionnaire collected standard information on a borrower's socio-demographic and non-socio demographic characteristics. In addition, it also collected information on borrower's civic and religious engagement, perception on trust, fairness, help, and bonding social capital. The second questionnaire collected information on borrower's personality traits, i.e. on the dispositional aspects of the borrower's behavior. To this effect, we used a 33 item instrument that is a brief version of the 44 item inventory (see John and Srivastava, 1999) of the five-factor model used in personality psychology. Each item constitutes a sentence containing an adjective that may or may not describe the individual and she is required to rate herself on each item using a Likert Scale from 1 to 5. The third questionnaire was a social network questionnaire. To answer the questions on this questionnaire, a respondent is provided with a list of all the contacts in her group and she is asked to indicate which contacts in the list came to her for advice or other forms of help, as well as, those she goes to for the specified advice or help. For each contact specified, the respondent is requested to also specify the type of relationship she shares with the named person.[8]

All the questionnaires, except the social network questionnaire which was administered in paper form, were administered using the mobile phone app magpi.[9]

[7]The randomization was done using excel. We first generated random numbers and then ordered (ascendingly) the randomly generated numbers and then selected the first 3 to 7 rows (in the case of intervention communities) and the first 1 to 3 rows (in the case of groups).

[8]The information from the social network question is not use in the current paper

[9]Magpi is a leading provider of configurable, cloud-based mobile collection, communication, and data visualization tools to let organizations improve the effectiveness of their mobile workforce and improve field operations, see http://home.magpi.com/about/

The interviews were carried out between October and December 2016 by a team of 5 enumerators with a single supervisor (the lead researcher). The enumerators were distributed across the four regions involve in the study and each covered about 4 villages. An enumerator was mandated to stay in a village until all the groups in the village are covered and all members of the group are interviewed. To facilitate their work in the field, they were all provided with smart phones and power banks. Every enumerator was required to upload all the questionnaires he collected in the magpi platform, on daily basis. The supervisor then checks the questionnaires and ensures that all errors, in the data collected, are addressed before the enumerator leaves a village.

Given that most of our respondents are illiterates and with little or no knowledge of the official language, English, all questionnaires were administered in the local language comfortably understood by the respondent.[10] In this regard, enumerators were used that are thoroughly conversant in the language widely spoken in the communities where they are sent. Furthermore, a two-day training of enumerators was also organized in which the lead researcher trained the enumerators on how to administer the survey instruments. This was done to ensure that the enumerators fully understand the survey instruments and are able to ask them in the local languages. Regarding the personality trait questionnaire, all trait adjectives use in the inventory were translated into the local language by the researcher via the assistance of a native speaker of the local language. In the event that an ambiguity arises in the meaning of an English adjective when translated in the local language, about 5 native speakers are randomly sought and ask about the meaning of the adjective in their local language. The most common interpretation given by these respondents is adopted as the appropriate meaning of that adjective in the local language. In selecting the enumerators, therefore, we put emphasis on being a native speaker of the local language to be used in administering the questionnaires and also obtaining a credit in English in the high school final examinations. These checks were instituted to ensure that the responses to the questions, especially those in the personality trait questionnaire, are not motivated by poor translation of the questions in the local language of the respondent by the enumerator.

Therefore, from an initial sample of 600 respondents, we got 528 responses and there were 72 non-responses; they couldn't be interviewed within the recall time frame stipulated. So, our response rate is about 82 percent. However, about 11 observations were further lost during the data cleaning. Thus, our final sample constitutes 517 individual observations. The total number of communities selected was 18 and about 34 groups were involved, out of which 20 were solidarity groups and 14 were large groups.

[10] Usually this is a language of the dominant tribe or ethnic group in the community where the interview was conducted.

3.1 The Big Five Inventory

In personality psychology, there is a generally agreed notion that only five or or six dimensions of personality are the source of much of the variation in human behavior, (Rustichini et al., 2016). Hence, the five-factor model, which measures personality by relying on five big dimensions, is the most widely used measure of personality traits. It involves the grouping of traits into mutually exclusive categories using approaches that originated from lexical hypothesis; an idea that was first used by (Galton, 1884). It is based on the premise that the most important traits in people lives can be expressed as single terms in their common language, (Goldberg, 1993). This means a good starting point for a "shared taxonomy is the natural language", (John et al., 2008). The idea that personality traits can be studied by grouping traits into mutually exclusive categories using terms from the common language came from the contributions of German psychologist (Baumgarten, 1933) and (Allport and Odbert, 1936).[11] The contribution of the former was stimulated by the work of another German Psychologist (Klages, 1926) who first hinted that the careful analysis of language could help in the understanding of personality trait, (Digman, 1990). The finding of these authors laid the ground for a common taxonomy of personality traits and emergence of personality trait measures such as FFM.

The Big or five-factor model involves the grouping of personality traits into five main domains, namely: extraversion, neuroticism, openness to experience, conscientiousness, and agreeableness. For the sake of preciseness, each of these domains could be further divided into facets. The development of the big five factor model of personality started with (Thurston, 1934) and Raymond Cartell, see (Cattell, 1943). It was developed further by several authors (such as Norman, 1963; Digman, 1963)). (McCrae and Costa Jr, 1985) built on the work of the previous contributors, particularly (Eysenck, 1970) who first introduced Neuroticism and Extraversion, and created a variant of the personality factor model called the NEO (for Neuroticism, Extroversion and Openness to experience; respectively) personality instrument. In (Costa and MacCrae, 1992), the NEO instrument was revised to include two more factors (Conscientiousness and Agreeableness) to make it a standard five-factor personality inventory.[12] Each of the domains constitutes numerous numbers of traits, (Goldberg, 1993). Extraversion measure how energetic an individual is and to what extent is the individual engaged with the world, as well as, the individuals' social attitude. Hence, it can be viewed as a contrast between traits such as activity level, assertiveness and talkativeness and traits such as being passive, reserve, and silence, (Goldberg, 1993). Neuroticism measures emotional instability, that is, the tendency of an individual to experience negative feeling or other forms of emotional discontent

[11] See (John et al., 2008) for details.

[12] See (Goldberg, 1993) for more elaboration.

such as anxiety, anger, or to suffer from stress. Therefore, it constitutes traits such as nervousness, moodiness, not contented, shyness, and not self-confident. Openness to experience measures the extent to which an individual is curious, imaginative, and appreciates new and unconventional ideas, as well as, being aesthetic or having excitable feelings. Conscientiousness is a measure of whether an individual has a sense of direction or not. Hence, it includes traits that capture things like competence, orderliness, dutifulness and deliberation and also self-discipline. Agreeableness measures the ability and tendency of an individual to cooperate with others as well as the level of altruism. It involves facets that measure cooperative behavior such as trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness.

In constructing our big five inventory, we rely on the approach of (Goldberg, 1990).[13] Hence, the Big Five Inventory (BFI) we use consists of 33 items and each domain or factor of the BFI is further divided an average of 5 personality facet. Therefore, our BFI constitutes, on average, of 30 different facets, and it is an abbreviated version of the 44 item BFI (see (John and Srivastava, 1999)).[14] At this point, it is worth noting that in using the big five instrument to study behavior, particularly in economics, many authors opt for a brief instrument rather than long instrument. The argument usually put forward as a basis for such a decision is that long instruments are costly to administer. However, the fact that long instruments have better psychometric features than short instruments, (Gosling et al., 2003), it is better to use the latter when it is ideal. It is for this reason that we decided to use a long instrument.

As indicated in the previous section, our data was collected by asking each individual to rate herself on each of the 33 items using a five-point Likert scale ranging from 1 (disagrees strongly) to 5 (Agrees strongly). The individual's score on each domain is derived from the average of her score on the items that constitute that domain. As different sub-groups have a different number of items, we standardized the scores around mean zero and standard deviation one. Given that we used scale based measures to collect information on variables that cannot be measured explicitly, it is a good practice to check for internal validity of these measures; via reliability measures such as the Crohnbach's alpha or factor analysis. As a result, we checked for internal consistency of the domains of our big five instrument using the Cronbach's alpha.[15] The results indicate a reliability index that ranges from 0.63 for openness to 0.75 for Conscientiousness (see appendix for details). The reliability

[13]The central difference between (Goldberg, 1990) big five instrument and other similar instruments of the five-factor model is that he assumed that the warmth facet captures more extraversion than agreeableness. Therefore, warmth is categorized in the extraversion group.

[14]This way of constructing the FFM was first proposed by (Costa and MacCrae, 1992) and is widely known as the NEO-PI-R (that is the revised NEO Personal Inventory).

[15](Bland and Altman, 1997) provide a brief and comprehensive introduction of the Crohnbach's alpha

indexes we obtained are less than those found by (John and Srivastava, 1999)), who reported that the reliability indexes for the 44 item BFI scales is between .75 and .90. The difference could be driven by the fact that we are using a brief instrument.[16]

4 Empirical Strategy

4.1 Model

we use a logit model to estimate the effect of differences in personality traits on the repayment behavior of a borrower. In the literature loan default is the main variable that is used to capture repayment behavior. It is, therefore, the most focused on outcome for researchers and practitioners, (Karlan, 2007). But in our case, we do not have a data on loan defaults as the credit provider do not have a proper record of such. Thus, we use delinquency measured by a borrower's self-report of whether she once fail to repay a loan on time or not as a proxy for default. This variable is coded as one for individual who report that they have not paid all the past loans on time and zero otherwise. As such a measure of default is somehow subjective, all self-reports are verified through the group heads. One might wonder why to verify through the group heads and not the credit officers. The motivation behind this is two-fold: first, the group heads are usually responsible for collecting individual repayments and hands them over to the loan officer who records the payment immediately on the GAWFA online loan recovery platform and gives the head, on behalf of the group, a receipt of repayment. This means the group heads are more informed about individual late repayments than the loan officer. Second, it sometimes occurs that an individual fails to repay on time but this is unknown to the loan officer as the group repays on time. This happens when the group head or some other member(s) of the group pays on behalf of a defaulted member to ensure that the group repays on time.

At the right side of our logit model, we have the personality trait variables, measured from the five-factor domain, and control variables. The personality traits are Extraversion, Agreeableness, conscientiousness, Neuroticism, and openness. We have two set of control variables: One controlling for individual differences in social capital and the other controlling for individual differences in cognitive traits such as age, education, marital status, and ownership of a business or income from owned business. The inclusion of social capital variables as a control variable is motivated by debates in the group lending literature (e.g Cassar et al., 2007; Ahlin and Townsend, 2007) that social capital affect repayment behavior. Hence, we can also test whether these variables matter for the borrower's repayment behavior. We mea-

[16]see (Mueller and Plug, 2006) for an explanation of how the number of items involve affect the reliability index of a measure.

sure social capital by asking respondents five questions around their bonding social capital that are reported on a Likert scale from 1 (it does not apply to me) to 5 (it very strongly apply to me). The five questions that measure bonding social capital are: "I live in a close-knit neighborhood," "People in neighborhood are are generally willing to help their neighbors," "People in my neighborhood don't like each other," "People in my neighborhood share the same value," "People in my neighborhood can be trusted." This method of measuring bonding social capital was first used by the Project on Human Development in Chicago Neighborhood (PHDCN), (Usher, 2005). The individual scores on the five items are averaged for each respondent to reach a unique index of social capital, called socindex in our dataset. The reliability index of this measure is about 0.69. The standardized score has a minimum value of -3.84 and a maximum value 1.73. Another method of measuring social capital that is used in the literature (e.g Karlan, 2005) is measuring individual social capital from three items in the generalized social survey (GSS in short) that captures individual perception on "trust," "fairness," and "helping." There is proven evidence that perception on these items is significantly related to real world outcomes, (Karlan, 2005). We also include them in our model to see whether they affect repayment behavior of the borrowers. In addition, we also combine the three items into a single measure called the gssindex. This was done by summing the respondent's reported score on each of the items and standardizing this around mean zero and variance one. The alpha coefficient of the items is 0.77 and the standardized scores have a minimum value of -2.94 and a maximum value of 2.30.

[table a2 and table a3 about here]

Hence, our logit model is of the following:

$$\log\left(\frac{P_i}{1-P_i}\right) = \alpha_1 + \sum_{i=1}^{P=5} \beta_{1i} x_{1i} + \sum_{i=1}^{Q=2} \beta_{2i} x_{2i} + \sum_{i=0}^{C=5} \beta_{3i} x_{3i} + \epsilon_i \tag{1}$$

where the x_1's denotes a set of $P = 5$ variables constituting of the 5 personality traits variables from our big five model, the x_{2i}'s denotes a set of $Q = 2$ variables that measures the social capital variables, and x_{3i}'s denotes set $C = 5$ control variables that measure the cognitive traits of the borrower. The variable P_i is the dependent variable representing the probability of not repaying measured from borrowers self-report on their past default. It is coded 0 if the individual reports that she has never defaulted on a past loan and 1 if the individual reported that she has defaulted, at least once, on a past loan. Note that default in our case means the individual was not able to repay a loan on time. One shortcoming of our measure of default is that it does not measure the repayment performance of the group, as individual late repayment sometimes does not lead to group default. However, if it(late repayment) is rampant it can affect group performance. For this reason, our measure can be a good proxy of how individual behavior might affect group outcomes and consequently the performance of a group-based lending scheme. Another short coming of our measure is that it is based on self-reports by the borrower, which is subjective. However, with reference to (Petrick, 2005), (Dufhues et al., 2012, 2013) highlighted that no "plausible argument" exist to presume that subjective information are less valid that other information in survey data. In this regard, we do not think the subjectivity of the individual reports invalidates our measure of default. Furthermore, the fact that self-reports by the borrower were verified through the group head, who collect individual repayments, increases the validity of our measure.

In estimating the model, we use three different specifications: In the first specification, we estimated a model with just the core critical variables. In the second specification, we included the social capital variables to the first specification. In the third specification, we added the cognitive trait variables, as control variables, to the second specification. For each of this specification, we ran a logit and a tobit model. The motivation for considering a tobit model is twofold: First, we believe our dependent variable could be truncated at zero. This is due to the noisy nature of our measure of default in that it is only observable for those that have reported that they have been late in repaying a past loan. For those that have reported that they were never late in repayment, we do not know if its true that never defaulted, despite our verification of the information via the group head. Our justification of using the tobit model is similar to that given by (Karlan, 2007). Second, we use the tobit model to check whether our initial model is robust against alternative specifications. The tobit specification for the default probability (D_i) is given as

$$D_i = a + \sum_{i=1}^{P=5} b_{1i}x_{1i} + \sum_{i=1}^{Q=2} b_{2i}x_{2i} + \sum_{i=0}^{C=5} b_{3i}x_{3i} + \upsilon_i \tag{2}$$

$$D_i^* = \begin{cases} 0, & \text{if } D_i \leqslant 0 \implies \textit{default=no} \\ 1, & \text{if } D_i > 0 \implies \textit{default=yes} \end{cases} \tag{3}$$

In this specification, we model individual default behavior as a latent variable D_i, which is observable only for those that reported their past defaults. The right-hand side variables have the same interpretation as in equation 1. In estimating all the models, we controlled for cluster effects and estimate the standard errors using the jackknife method; first introduced by (Quenouille, 1956) and extended by (Tukey, 1958) for variance estimation. As a repeated sampling technique, the jackknife is robust in small samples.

Given that not all borrowers in the sample have taken a loan, this could lead to selection bias in our model. we check for this by estimating the model using the Heckman two-stage procedure. In the first stage, we ran a probit model to determine the probability of taking a loan. This first stage regression is commonly referred to as the selection model, and it is used for getting the inverse mill ratio. Before running the selection model is it important to the variables that affect selection. Using a step wise regression approach, we found that the two factors that significantly determine the probability of taking a loan are age and whether the individual has an immediate family member living abroad. In the second stage, therefore, we estimate the main model including the inverse mill ratio. This procedure helps us to address selection bias. The results from these estimations are shown in table 4.

4.2 Identification Issues

In relating "group outcomes" to individual borrower's characteristics, (Karlan, 2007) has highlighted two identification concerns that are due to peer-selection by borrowers into borrowing groups; omitted variable bias and simultaneity bias. Omitted variables bias arises because self-selection means individual join groups on the basis of characteristics that are not observable to the researcher, which could correlate with both the observed characteristics as well as group outcomes. Simultaneity bias, on the other hand, arises when the relationship between the individual characteristic and group outcomes can be inferred in both directions. A good example is where successful groups lead to better social relations, hence, the direction of causation between group outcomes and social relations occurs in both ways. As a result, causal inference is ambiguous. [17] Since we use social capital measures in specification II and III, simultaneity bias could be a concern in these models. However, our measures of social capital are based on borrowers generalized perception on trust or help or fairness, and there is ample evidence that measures based on generalized perceptions on trust and help are determined by village level outcomes that are independent of individual or group level outcomes. In this regard, our measures of social capital can be seen as exogenous. Thus, we do not worry about simultaneity bias attributed to these variables.

Regarding omitted variable bias, this could be a concern in our model if it is true that individuals with higher traits are more likely to join groups. For traits like agreeableness, this could mean individuals who have higher willingness to cooperate with others are more likely to join groups and therefore repays more. Thus, failure to account for such an unobserved effect will lead to endogeneity problems. In this regard, we checked for whether omitted variable bias is a problem in our model by doing the following: first, we determine whether the individual participates in any of the following three groups; religious, political, and other loan groups. second, we

[17] see (Karlan, 2007) for detail discussions.

relate personality traits to the probability of joining these groups and check if any significant relationship exist. If a significant relation exists we could that personality trait is important for group selection; otherwise, we conclude that it is irrelevant for group selection. The underlying assumption of this exercise is that if traits are relevant in group selection, then, we should observe a positive effect on personality traits and the probability of joining a group. The results of this estimation are shown in table 8. From this exercise, we found that none of the personality traits has a significant positive effect on the probability of joining a group. We use this as a naive evidence that omitted variable bias due to peer selection is not a fundamental problem for our model.

5 Analysis of Empirical Results

The characteristics of the borrowers in our sample are reported in table 2. For the borrowers in the final sample, about 83% have reported that they have already received their first loan from GAWFA. More than 70% of the borrowers are participants in LG loans. The average value of the loan taken is about 2561 Dalasi (about $60) and more than 50% of the borrowers have received at least this amount from the last loan taken. Among those that received a loan from GAWFA, about 31% have reported that they have once defaulted on a pass loan. The average age of the borrowers in our sample is about 41 years, and about 38% are above the mean age. Only 25% of the borrowers have attended any form of formal education. The rate of business ownership among borrowers is about 51%. The majority of the business owners, more than 60%, are engaged in petty trading including the selling of agricultural produce.

[Insert table 1 about here]

In table 3, we compare the descriptive statistics on the critical core and social capital variables between defaulters and non-defaulters. The results show that, except for Neuroticism, the mean score on each of the domains of our big five inventory is higher for non-defaulters than defaulters. However, only the difference in the mean score of agreeableness is significant at 95% confidence level. The mean difference in Extraversion and Openness are significant only at 90% confidence level, and for Conscientiousness and Neuroticism, the mean difference between the two groups is not significant.In addition, the results also indicate that the individuals or borrowers that repay on time have a higher mean score on bonding social capital than individual that do not repay on time. The mean difference between the groups on social capital is highly significant.

[Insert table 2 about here]

5.1 The effect of the Big five on default probability

Table 5 reports the results from the regressions. For all the three specifications, we see that the logit and tobit results are quite consistent in terms of both sign, size, and significant. The tobit results, however, seems more conservative than the logit results. In any case, we find that controlling for possible truncation in the data on defaults do not significantly affect our results. Furthermore, we also find that controlling for social capital and cognitive trait variables improve the results; as our Pseudo R^2 increase with the addition of these variables to the first specification.

Since model III constitute the main specification of interest, we focus our discussions on the logit results of this model. With the exception of Conscientiousness, we found that all the domains of our measure of personality traits have a negative effect on the probability of default. Extraversion is associated with about 0.05 decrease in the probability of default and it has a weak statistical significance of 10%. Hence, borrowers that are more sociable and active are about 5 percent less likely to default than borrowers who score low on these traits. As expected, Agreeableness, which is related to cooperative and trusting attitude, decreases the probability of default by about 0.23, which is statistically at 5%. Conscientiousness increases the probability of default for about 0.004, but this is not statistically significant. As conscientiousness is associated with traits such as being hardworking or organized or planful, it is surprising that having such traits has a positive impact on the probability of default. A higher level of Neuroticism is also negatively associated with the probability of default and it is statistically significant at 5%. What this means is that individuals that are emotionally unstable are less likely to default. This is somehow intuitive as it indicates that individuals who know that they can easily get depressed or angered by the action of other towards them when do not pay their debts on time are more probable to pay on time. They pay because they do not want to experience negative emotions associated with late repayment. Openness to experience is associated with 0.08 decrease in the probability of default, which is also statistically significant at 10%. The negative relationship between default and openness to experience is consistent with our apriori expectation. When you are a business owner, true for more than 50 percent of the borrowers in our sample, then Openness to Experience could mean willingness to take risk. There is extensive evidence in the finance and management literature that willingness to take risk is positively related to business success. For this reason, high level of Openness to Experience should be associated with decrease probability of default, which is what we found. The marginal effects of the variables on the default probability are reported in figure 1.

[table 3 about here]

5.2 The impact of cognitive trait

The estimation results on the predictive power of the cognitive trait variables on the probability of default are reported in table 7. We see that the logit results do not differ extensively from the tobit results, even though, the latter are more conservative. The result indicates that being educated is positively associated with the probability of default and it is highly statistically significant. This is against our expectation and the existing empirical evidence. However, this could be motivated by the fact that education is negatively related with informal business (See Jimenez et al., 2015) and in developing countries, informal business is more rampant. Thus, when money is borrowed and it is not used to set up or bolster an informal business then it is more likely to spend it unproductively, which reduces the probability of repaying it.

As expected, owning a business decreases the probability of default for about 0.63. This effect decreases by almost half and becomes more statistically significant when we control for truncation in our dependent variable. Owning a business is akin to the productive use of the loan and therefore it should not be far fetched that it reduces the probability of default. We also find that age is negatively related to default probability and it is highly statistically significant. What this means is that older borrowers are more likely to repay their loan than younger borrowers. A similar finding is reported by (Mokhtar et al., 2012) and they provided two explanations for this: One, older borrowers are more experience in business than younger borrowers, hence, they are less likely to face repayment difficulties associated with business failure. Two, being young increases the believe that you can get a loan from another microcredit provider even if you once defaulted with other providers. A third explanation could be that older women see their microcredit loans as the only source of external financing to bolster their business while young women have other means of external financing.

With regards to group size, we found that being a member of a small group is increases the probability of having problems with repaying a loan, which is highly significant. This finding is in contrast with the evidence in the literature (e.g Abbink et al., 2006) that larger group size is associated with higher repayment problems due the moral hazard problem; as group size increases peer monitoring becomes more costly, thus, increasing default probability. But, (Ahlin, 2015) theoretically demonstrated that under adverse selection higher group size lead to higher loan repayment; depending on the amount of social capital that exist within groups. In this regard, the impact of group size on loan repayment is not clear cut. However, our results are consisted with (Ahlin, 2015).

For social capital variables, table 6 shows that both our measure of bonding social capital and the GSS measure of social capital are associated with negative default probability and are highly significant. Therefore, consistent with the evidence in the literature briefly discussed in section 4.1, we also found evidence that higher social capital motivates higher loan repayment.

6 Conclusion

In analyzing the performance of microcredit program, it is intuitively apparent that two broad factors are paramount; cognitive and non-cognitive factors of the borrowers. However, much of the focus in the group lending literature has been on studying the impact of cognitive traits of borrowers on their repayment behavior. Despite the fact that there has been a surge of interest to understand how non-cognitive traits affect the behavior of economic actor not many studies exist that focuses on the impact of these traits on behavior in credit markets; in particular, microcredit markets in developing countries. The aim of our paper was to feel this gap. Using a data collected from an NGO group based mocrocredit program targeting only women in Gambia, we find evidence that personality traits measured from the five factor model do affect behavior borrowers in micro-lending programs. In this regard, our results differ from KMR, who found no strong evidence that these traits affect behavior. Therefore, our evidence suggests that adverse selection problems in microcredit cannot be ignored; especially in developing countries.

Among the five domains measuring personality traits in the big five inventory, we found evidence that all factors, except Conscientiousness, do influence default behavior. However, the strongest impacts were found for Agreeableness and Neuroticism. The evidence that traits like Agreeableness significantly affect repayment behavior in group-based lending schemes is captivating; as cooperation among members of a group, in terms of monitoring each other, is among the core factors that explains the success of group-based lending. Thus, if microcredit providers could sort borrowers according to these traits, they could improve the performance of their schemes. Furthermore, this means incorporating tools that reveal borrowers non-cognitive traits in microcredit programs will lead to better performance. Aside from the personality traits, we also find evidence that social capital matters for repayment behavior. In addition, other cognitive traits such as age, business ownership, and education also matter.

Our study is without limitation. The first limitation is that we do not have a structural model from where we can infer that the relationship between personality traits and default behavior is a causal one. This also affects the external validity of our results. Therefore, any further research in this direction could help us better understand the impact of personality traits on behavior of microcredit borrowers. The second limitation is that we rely on a very restrictive assumption to argue for the independence our personality trait variables and we do not have sufficient information to test the reliability of this assumption. The third limitation is that our reliability indices for the elements of our big five inventory are not as high as is predicted in the literature. This could be due to the fact that we are using a brief an instrument; although not brief when compared to many studies that use the big five instruments. The fourth limitation is that our study is based on just borrowers in a lending scheme that targets just women. Hence, we could not look at whether gender differences in personality traits matters for repayment behavior.We leave this for future research.

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Table 1: Reliability index of GSSindex

Interim correlations-Crohnbach Alpha			
	GSS1	GSS2	GSS3
GSS1	1.00		
GSS2	0.56	1.00	
GSS3	0.49	0.53	1.00
Alpha			0.77

Table 2: Reliability index of Social capital index

Interim correlations-Crohnbach Alpha					
	knit	aidneig	hate*	samval	trust
knit	1.00				
aidneig	0.34	1.00			
hate	0.26	0.41	1.00		
samval	0.12	0.18	0.27	1.00	
trust	0.30	0.50	0.34	0.07	1.00
Alpha					0.69

* The scales on this measure are reversed.
See table 2 for the description of variables.

Table 3: Summary Statistics
Critical Core Variables and Social Capital Variables

	Never defaulted		Once defaulted		Sign. of mean diff.
	mean & std error	std. dev. & no. of Obs	mean std error	std. dev. & no. of Obs	p-values*
ExTra	9.22	4.21	8.66	4.17	0.08
	(0.14)	$n = 294$	(0.16)	$n = 129$	
AgRea	14.54	3.35	13.48	3.80	0.01
	(0.22)	$n = 294$	(0.27)	$n = 130$	
ConSci	13.11	3.92	12.88	3.99	0.65
	(0.29)	$n = 291$	(0.28)	$n = 130$	
NeuTis	2.14	3.68	2.19	4.34	0.44
	(0.17)	$n = 294$	(0.23)	$n = 130$	
Open	22.71	4.55	22.01	4.18	0.08
	(0.16)	$n = 293$	(0.19)	$n = 130$	
socindex	20.30	2.70	19.06	3.47	0.00
	(0.11)	$n = 296$	(0.17)	$n = 130$	
gssindex	0.53	1.10	0.07	1.18	0.00
	(0.04)	$n = 296$	(0.04)	$n = 130$	

For each variable, the Table reports the mean, the Jackknife standard error of the estimate of the mean, the standard deviation, and the number of observations in each sub-sample used to obtain the summary statistic. Also reported are the the p-values from a t-test of a statistical significance of difference in means between the two groups.

* The p-values reported are the two tailed test p-values.

Table 4: Summary Statistics(*All Variables*)

	Mean	std. dev.	N
Dependent variable			
paid= Did you always pay your loan on time? (yes=0, no=1)	0.31	0.46	426
Independent variables			
Core critical variables			
ExTra= Extraversion	9.27	4.13	513
AgRea= Agreeableness	14.22	3.50	514
ConSci= Conscientiousness	13.34	3.94	511
NeuTis= Neurotiscism	1.97	3.91	514
Open= Openness to experience	22.67	4.38	513
Social capital variables			
gss1= People can be trusted	0.31	0.84	517
gss2= people try to be fair	-0.18	0.88	517
gss3= people are helpful	0.25	0.87	517
gssindex*	0.37	1.15	517
knit= Lives in a close knit neighborhood	4.49	0.84	517
aidneig= Neighbors helpful to one another	4.50	0.94	517
hate= Neighbors don't like each other	2.60	1.09	517
samval= Neighbors share same value)	2.23	2.30	517
trust= Neighbors are trustful	4.41	1.09	517
socindex**	20.02	2.87	517
Other control variables			
married= marital status(married=1, not married=0)	0.87	0.48	517
age	40.59	14.29	513
educa= attended school (yes=1, no=0)	0.25	0.43	517
yedu= year of education	7.23	3.99	128
lonval= value of last loan	2561.00	2861.72	400
ownbuz= Ownership of business (yes=1, no=0)	0.57	0.50	517
Other variables			
reloan= received first loan(yes=1, no=0)	0.83	.38	517
fabrd= has a family member abroad(yes=1, no=0)	.50	.50	517
grotyp = group type (LG=1, SG=2)	1.28	0.45	517

* The gssindex is calculated as the average score of the responses to gss1, gss2, and gss3. Note in the estimation we use the standardized score of the sum of the three, which are denoted with the subscript a1 added to the names.

** Like the gssindex, the socindex is also computed as the average score of the responses to the five bonding social capital questions. The response range from 1 (disagree strongly) to 5 (agree strongly), and the response scales for hate are reversed.

Table 5: Borrowers Default Behavior

	Dependent Variable: Individual default					
	Model I		Model II		Model III	
	logit	tobit	logit	tobit	logit	tobit
ExTra_{a1}	-0.149***	-0.103***	-0.140***	-0.088***	-0.054*	-0.051*
	(0.038)	(0.028)	(0.032)	(0.021)	(0.044)	(0.029)
AgRea_{a1}	-0.353***	-0.236***	-0.231***	-0.150**	-0.228**	-0.138**
	(0.071)	(0.053)	(0.075)	(0.051)	(0.081)	(0.052)
ConSci_{a1}	0.110	0.084	0.061	0.040	0.004	-0.000
	(0.089)	(0.060)	(0.084)	(0.053)	(0.082)	(0.048)
NeuTis_{a1}	-0.125*	-0.088*	-0.130*	-0.094*	-0.173**	-0.110**
	(0.066)	(0.043)	(0.069)	(0.045)	(0.075)	(0.044)
Open_{a1}	-0.119**	-0.091**	-0.049	-0.038	-0.080*	-0.056*
	(0.052)	(0.038)	(0.048)	(0.034)	(0.044)	(0.028)
socindex			-0.096***	-0.058***	-0.102***	-0.059***
			(0.017)	(0.010)	(0.019)	(0.010)
gssindex			-0.337***	-0.213***	-0.320***	-0.200***
			(0.047)	(0.027)	(0.051)	(0.028)
sigma		1.202***		1.166***		1.136
		(0.037)		(0.037)		(0.040)***
Other Controls included	no	no	no	no	yes	yes
Pseudo R^2	0.03	0.02	0.06	0.04	0.11	0.07
F stats.	11.34	8.94	12.93	12.35	23.36	13.09
N	419	419	419	419	419	419

*** 99% significance; ** 95% significance; *90% significance.

Reported in parenthesis are the jackknife standard error that corrects for clustering at the village level.

Table 6: Controlling for Selection bias

Dependent Variable: Individual default		
	logit	Heckmann
ExTra_{a1}	-0.088*	-0.018*
	(0.044)	(0.009)
AgRea_{a1}	-0.228**	-0.046**
	(0.081)	(0.018)
ConSci_{a1}	0.004	-0.000
	(0.082)	(0.011)
NeuTis_{a1}	-0.173**	-0.032**
	(0.075)	(0.013)
Open_{a1}	-0.080*	-0.016*
	(0.044)	(0.008)
socindex	-0.102***	-0.021***
	(0.019)	(0.006)
gssindex	-0.320***	-0.060***
	(0.051)	(0.015)
educa	0.409***	0.083***
	(0.069)	(0.025)
ownbuz	-0.464**	-0.090**
	(0.195)	(0.038)
age	-0.014***	-0.003***
	(0.003)	(0.001)
married	-0.025	-0.014
	(0.199)	(0.034)
fabrd	-0.042	-0.003
	(0.095)	(0.030)
grotype (SG)	0.473**	0.160***
	(0.165)	(0.053)
athrho		-0.024
		(5.115)
lnsigma		-0.824***
		(0.044)
F stats	23.36	20.53
N	419	504

*** 99% significance; ** 95% significance; *90% significance.
Reported in parenthesis are the jackknife standard error that corrects for clustering at the village level.

Table 7: Borrowers Default Behavior
Cognitive trait variables

	Dependent Variable: Individual default	
	logit	tobit
educa-yes	0.428***	0.262***
	(0.071)	(0.046)
ownbuz-yes	-0.625**	-0.339***
	(0.221)	(0.122)
age	-0.014***	-0.008***
	(0.003)	(0.001)
married-yes	0.037	0.052
	(0.200)	(0.115)
fabrd-yes	-0.006	0.024
	(0.096)	(0.062)
grotyp-SG	0.810**	0.474**
	(0.281))	(0.163)
Pseudo R^2	0.11	0.07
F stats.	23.36	13.09
N	419	419

*** 99% significance; ** 95% significance; *90% significance.
Reported in parenthesis are the jackknife standard error that corrects for clustering at the village level.

Table 8: Determinant of joining a group

	Dependent Variable: member of groups[†]
	logit
$\text{NeuTis}_a 1$	0.218
	(0.127)
$\text{Open}_a 1$	0.019
	(0.129)
$\text{ConSci}_a 1$	0.213
	(0.136)
$\text{AgRea}_a 1$	-0.253
	(0.149)
$\text{ExTra}_a 1$	-0.321*
	(0.119)
controls added[‡]	yes
Pseudo R^2	0.13
LR $chi2$	90.44
N	500

*90% significance.

[†] Membership in the following three groups is considered: Religion, political, and other loan groups.

[‡] The control variables included were age marital status education and ethnicity.

Figure 1: marginal effects of critical core variables (logit of model III)