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Non-farm Entrepreneurial Activities and the role of Non-cognitive Skills in Agriculture. Theoretical framework and Empirical Evidence from Ethiopia.

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INTRODUCTION

Background and Motivations:

SSA economic development and Ethiopia case study

The world can be easily divided into areas of wealth and poverty. This has always been true. Since after the colonial rule, economic strategies implemented by wealthier countries and donors in Sub-Saharan Africa (SSA) aimed to increase economic growth in poor nations in the continent. In the 60s a number of SSA countries had relatively promising development expectations and income levels similar to those in Southeast Asian countries [Heidhues, 2009]. At that time, World Bank (WB) data reported that GDP per capita and GDP growth were higher in Africa than in Asia: due to their superior endowment of natural resource SSA countries were expected to grow faster than Asian countries [World Bank, 2005 p.274]. However, in the second decade of the 2000s many Southeast Asian countries achieved higher development and income levels, some even reaching the status of ``semi-industrialized'' countries, while for many SSA countries the political and economic stability are still distant promises to fulfill [Heidhues, *ibid*.]. Why? SSA for over two decades (70s-80s) missed the opportunity to adjust to the global changing economic conditions and lost the chance to grow [Sundaram et al., 2011]. In the 70s, massive food imports due to a drop in agricultural production, jointly with adverse terms of trade, oil crisis, a worsening of the world economy exacerbated the negative trends of social and economic indicators of SSA. At the same time, the political instability, ethnic conflicts and violence threatened the stability of the newborn African institutions. In the 80s, as Heidhues (*ibid*.) reports ``Africa's crisis was deepening with weak agricultural growth, declining industrial output, poor export performance, climbing internal and external debt as well as deteriorating social indicators, institutions and environment''. Not surprisingly, the literature refers to this period as `Africa's growth tragedy' [Easterly and Levine, 1997]. Until the late 90s, many economists warned against the persistence of slow growth in the continent [Sachs and Warner, 1997; Collier and Gunning 1999]. On the other hand, there is a general consensus that SSA experienced during the 2000s an unprecedented decade of economic growth, Young (2012) described it as an `African growth miracle'. Despite the progress made in reducing poverty[1] and achieving nutrition objectives, Africa remains the least developed region in the world. A significant share of economic growth was driven by reallocation of the workforce out of agriculture and towards modern sectors of the economy. However, agriculture still plays a crucial role in most of the economies of SSA countries. During the 2000s, the efforts to reduce poverty emphasized agricultural and rural development as fundamental players to foster development in Africa. This culminated in the WB's *World Development Report* 2008 which put agricultural at a central role for achieving the Millennium Development Goal.

A twofold strategy needs to be addressed in SSA. First, foster the modernization of the agricultural sector to increase the agricultural productivity in order to release labor force to other modern sectors of the economy. At the same time, this will generate an increase the wellbeing of households involved in farming activities. In fact, a technological improvement on the farm will help to increase the returns earned from these activities.

[1] The headcount ratio in Africa since 2002 declined by more than a fourth falling to 41% in 2013 (African Union, 2017)

Second, sustain the structural change. McMillan and Rodrik (2011) empirically show what Arthur Lewis originally hypothesized. They argue that:

> ``One of the earliest and most central insights of the literature on economic development is that development entails structural change. The countries that manage to pull out of poverty and get richer are those that are able to diversify away from agriculture and other traditional products. As labor and other resources move from agriculture into modern economic activities, overall productivity rises and income expand. The speed with which this structural transformation takes place is the key factor that differentiates successful countries from unsuccessful one''.

This urge for economic development calls for several focused reforms and essential investments in SSA. Amongst the most pressing for policy-makers we find:

- Regulatory and operational improvements for business and programs to attract foreign investment as well as stable governance (legal rights enforcement);
- Build infrastructure, reliable transport networks and power supply;
- Investing in the development of rural-urban economic linkages (i.e. processing of agricultural products);
- Increase investment in research and development to boost productivity in terms of efficiency and competitiveness with technological improvements (i.e. agricultural input adoption on farm, develop modern industry sector);
- Develop and sustain credit and financing systems;
- Provision of social infrastructure and improving the status of women still segregated to sectors with lower productivity and less remunerative.

Ethiopia is not an exception amongst other SSA countries. Compared to the common colonial experience of other SSA countries, Ethiopia experienced brief Italian occupation from 1935 to 1941 and can be actually considered a non-colony country. As Alemayehu (2007) extensively analyzed there were significant elements of modernization undertaken in terms of transportation during the Italian occupation. However, economic insecurity pervaded since then Ethiopia's modern history. During the Imperial Regime (1930-1974) the landed aristocracy and the majority of peasants constitute the major socio-economic agents during this period. Attempts were made to modernize the country through the expansion of school and health facilities, infrastructure and the promulgation of a constitution. However, during the consequent Derg (meaning `the committee' in Amharic) regime economic growth decelerated due to conflicts and its dependence on the agricultural sector. The Derg established a `hard control' socialist regime where market forces were deliberately repressed and socialization of the production and distribution process pursued vigorously. Only after 1991, adjustment policies of market liberalization were adopted. Impressive but fragile economic growth was reached due to external shocks (i.e. the war with Eritrea).

Ethiopia is among the most populous countries in SSA, with a population of 97 million of which 80% live in rural areas (World Bank databank, 2016). Ethiopia has witnessed rapid economic growth, with real gross domestic product (GDP) growth averaging 10.9% between 2004 and 2014, which has lifted the country from being among the poorest in the world in 2000 to be in a position to become a middle-income country by 2025 provided it continues its current growth trajectory [World Bank, 2015]. Since 2000, households have experienced a decade of remarkable progress in well-being and the country has seen a 33% reduction in the share of the population living in poverty, only Uganda has had a higher annual poverty reduction during the same time period [World Bank, Ethiopia Poverty Assessment, 2014]. However, almost 30% of Ethiopians still live below the nationally defined poverty line and malnutrition is very widespread damaging over one-third of total population [Ministry of Finance and Economic Development (MoFED), 2012; World Bank databank, 2016, respectively]. Agriculture is the major employer in the country and generates the largest share of valued added on total GDP (almost the 41%). Even though the efforts of the national government in boosting agricultural productivity with community shops, efforts to stabilize the volatility of food prices and subsidizing fertilizer farmers still struggle to abandon a subsistent farming system. Crop agriculture is dominated by smallholders with no further expansion of crop cultivation: production growth needs to come from yield improvements resulting from improved seeds and fertilizer. On the other hand, the rural non-farm sector has gained importance during the last years. From National Accounts a range of 10-35% of rural households in Ethiopia is engaged in non-farm enterprise indicating that Ethiopia is making effort to differentiate its economy away from agriculture. However, external constraints prevent the non-farm sector to further develop due to the high bribery index, the high number of days required to obtain an electrical connection, to start a business, the number of procedures to register a business [World Development Indicators, World Bank Doing Business and World Enterprise Survey data].

Research questions

The aim of the following chapters is to address **two main research questions**:

1. Emotional factors could affect decision-making, which is the role **of non-cognitive skills** in affecting **productive and allocative efficiency** in rural Ethiopia?

2. What are the **determinants** of Ethiopian households' **diversification** into **non-farm activities**? Are households *pushed/pulled* into these activities?

Regarding the first research question, the behavioral economics literature has provided ample empirical evidence sustaining the importance of emotional factors affecting individual decision-making. Since the seminal works of Simon and Kahneman until the more recent contributions of Heckman on the topic solid evidence on the importance of emotions affecting deviations of individual from rational decision-making has been produced for developed economies. What about developing countries? Recently, the behavioral economics approach has spread also outside Western countries. Given the positive responses and results that these first attempts brought they merited the enthusiastic epithet of `small miracles' by WB *World Development Report* 2015. One could argue if other empirical evidence is necessary to further stress what other researchers have proved until now. In fact, we could agree that all decision-makers -either rich or poor- could exhibit a bounded rationality proposed by Simon (1955) or rather the automatic thinking suggested by Kahneman (2003)[2]. However, a striking difference respect developed world is that in many developing countries -especially in SSA- poverty is a concrete bundle affecting with overwhelming consequences the living of millions of people. In fact, poor people may suffer the psychological stresses of poverty and scarcity providing them further impediments to the understanding of opportunities they face. Moreover, within the behavioral economics approach controlling for non-cognitive skills in analyzing farm production outcomes remains novel. As we before-mentioned, agriculture is the major employer in SSA and provides the livelihoods for millions of people. Since the 60s donors and national governments undertook efforts to replicate the success of the Asian Green Revolution. However, these policies have generated little effect in terms of increased use of chemical fertilizers or high yielding varieties. In part, this failure may be due to the different conditions in Africa compared to Asia. For instance, the African continent's agro-ecological zones are more diverse than those in Asia. However, could other factors have concurred to these disappointing results in boosting

[2] Bounded rationality is the idea developed by Simon that when individuals make decisions their rationality is limited by the tractability of the decision problem, the cognitive limitations of their minds and the time available to make the decision. This would lead to choose sub-optimal strategies. While, automatic thinking is one of the two thought systems defined by Kahneman affecting the decision making of the individual. It is defined to be fast, emotional, based on stereotypes and uses heuristics and `mental shortcut' to solve problems. The combination of these two systems -one fast and the other slow, effortful and calculating- defines the individual behavior. Depending on external conditions one of the two may prevail leading to different results given the same inputs.

agricultural productivity? Neglecting the effect of non-cognitive skills endowment on individual decision-making in developing rural context may overestimate the possible results of such policies promoting agricultural input usage? We put aside for a moment the desperate need of SSA for infrastructure the lack thereof hinders further economic development in the continent. Policies aiming to increase the supply and the availability of agricultural inputs to psychologically distressed farmers due to the difficult external conditions (poverty, drought, famine, conflicts and political instability) could not bring the expected results. It is difficult to see how policy-makers might alter those behavioral patterns which prevent farmers from reaching the technological frontier. Bernard et al. (2012) suggested that fatalistic beliefs have implications for the behavior of poor rural Ethiopian household towards investments in the future and hindering the consequent economic performance. The inclusion of farmers' behavioral traits to proxy traits which are difficult to systematically measure such as motivation, entrepreneurship and aspiration may help to understand rural smallholders' farming process and better target households more inclined to use new agricultural technologies.

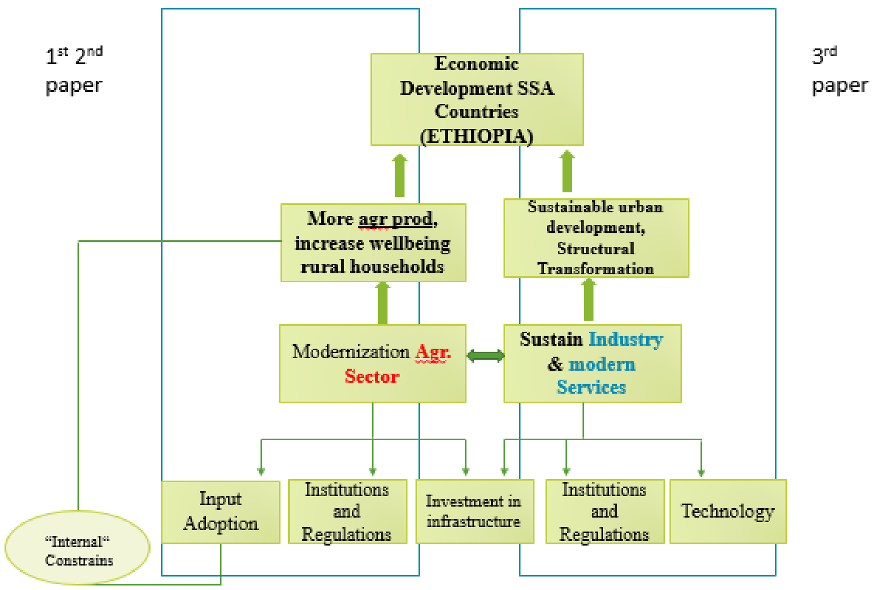
These considerations suggest that further research on the topic is needed. We present two papers trying to give a useful contribution to the related literature. We address two issues: a) the role of non-cognitive skills in affecting productive efficiency (the ability to produce more from the same inputs); b) how non-cognitive skills affect allocative efficiency (use of a more or less efficient combination of inputs). We proxy non-cognitive skills using taxonomies of traits derived from two well-known psychometric tests: the `Big Five Inventory' and the `Emotion Regulation' questionnaires. The endowment of either cognitive (years of education) and non-cognitive skills (conscientiousness and willingness to work for long-term goals) could affect the performance on a certain task. For instance, without enduring personality traits or strong cognitive abilities may be more likely to abandon agricultural activities. In the two following papers, we explore in a systematic way which behavioral traits are associated with higher yield output or with input adoption choices of Ethiopian rural smallholders. Non-cognitive skills can help answer why entrepreneurship appears to be limited in poor countries and help identifies what can be done to stimulate greater agricultural activity.

The second research question was motivated by complementing how off-farm income may sustain overall economic development in Ethiopia. The first research question focuses on agricultural productivity of rural farmers and their non-cognitive skills. However, the movement of workforce away from agriculture to manufacturing and industry is consistent with a long tradition in development economics in which poor countries need to undergo a process of structural change to achieve high levels of aggregate productivity. Following Lewis (1954) and Ranis and Fei (1961) seminal studies on the topic labor move from the less productive agricultural sector to the more productive ones, thus the economy grows in terms of productivity, income and the urbanization rate rises. However, in SSA most poverty alleviation strategies focus primarily only on smallholders' agricultural activity. A `pessimistic' school of agricultural development specialists thinks that for both technical and economic reasons, Africa cannot rely on agriculture as a source of growth or poverty reduction [Maxwell, 2004]. Evidence shows that close to 40% of African rural households are involved in non-farm activities despite the fact that only 9-19% of the rural labor force is employed in such activities [Haggblade et al., 2007]. According to Rijkers et al. (2008), non-farm activity in Ethiopia is predominantly a means to complement farm income rather than a pathway out of poverty. Understanding the determinants of households' participation in the non-farm sector[3] can be extremely useful for policy-makers determine which kind of policies to pursue to encourage the movement of labor across different sectors. Do households choose to allocate more labor off-farm because of the presence of more remunerative opportunities or rather have they pushed away from agriculture because of shocks harming agricultural output? Understanding the drivers behind households' participation in the non-farm sector enable us to further explore which benefits this engagement will bring to the households' wellbeing. Theoretically speaking the related literature tends to agree

[3] A variety of terms is used in the current literature to distinguish between different sources of rural income: `off-farm', `non-farm', `non-agricultural', in this dissertation we adopt the definition of `non-farm' income which refers to earning deriving from non-farm entrepreneurship activities

that households' income diversification will help households to cope better with shocks and increase the disposable income. Empirical evidence suggests either a positive or a negative correlation between non-farm income and wealth indicators. In the last paper presented in this dissertation, we want to give a picture of the current Ethiopian households' non-farm participation and the possible effect of this engagement on food consumption and agricultural input adoption. Even though the great progress toward achieving the Millennium Development Goals malnutrition damages over one-third of the total population in Ethiopia.

Conceptual Map: Background and Motivations



This conceptual map represents a broad simplification of the background and the motivations for this dissertation. Two are the main channels to reach the ambitious aim of economic development in SSA countries (and in this case the Ethiopian's one): through the modernization of the agricultural sector and helping the creation of industry, manufacturing and modern services. On one hand, agriculture accounts for the largest share of employed people and also for the largest proportion of value added generated as a percentage of total GDP. Most poverty alleviation strategies in Africa tend to focus on smallholders' agricultural activity. With the modernization of the agricultural sector, the agricultural production can be increased. Moreover, thanks to the technological improvement on farm agriculture may become a more remunerative activity for those households primarily involved in it. The increased labor productivity on the farm may help to release extra labor force away from agriculture towards modern sectors of the economy leading to a consequent increase in national GDP. As before-mentioned, one of the most central insights of development economics literature is that economic development entails a structural transformation. The countries that manage to pull out of poverty and get richer are those that are able to diversify away from agriculture and other traditional products. As labor and other resources move from agriculture into modern economic activities, overall productivity rises and income expand. The speed with which this structural transformation takes place is the key factor that differentiates successful countries from unsuccessful ones. The first two papers of this dissertation focus on the left side of the map: how `internal constraints' (personality traits) affect input adoption and agricultural productivity; while the third paper focuses on the right side. The paper explores whether non-farm entrepreneurship activities might help a successful structural transformation to occur in Ethiopia through a sustained diversification of households' income.

Methodology

The methodology used for this dissertation relies on different data sources. We provide for descriptive purposes descriptive statistics at the macro level provided by online sources such as FAO-stat and World Bank databank. We present data on Ethiopia and other SSA countries in order to complement the empirical estimation of the three papers performed at the microeconomic level using Ethiopian households' surveys.

To answer the **first research question**, we use cross-sectional data for 501 rural households collected in 2012. The survey was financed by FAO and implemented by the University of Addis Ababa in collaboration with CEIS of the University of TorVergata. The survey complements the usual information on demographic characteristics of the household, agricultural production, and labor activities with a special section devolved to collect data on individual non-cognitive characteristics. The `Big Five Inventory' and the `Emotion Regulation' questionnaires were used to proxy such individual characteristics. We use the scores for personality traits in the OLS estimation of the production function of the agricultural output and as controls for the probability of a household to adopt fertilizers and seeds on the plot. Then, we tested the neoclassical recursivity assumption strategy between input decisions and harvest outcome. We are aware of the limitations that such a small sample could generate as the limited external validity of our results. However, even though the sample is not representative for Ethiopa as a whole, we believe that this empirical exercise contributes new knowledge because it is one of the first study on the matter promoting an innovative angle of reading.

The methodology used for the **second research question** relies on longitudinal dataset `Living Standards Measurement Study-Integrated Survey on Agriculture' (LSMS-ISA) 2012, 2014 and 2016 available rounds. First of all, we provide from a descriptive point of view which socio-economic characteristics affect households that engage in the non-farm sector compared to those households who do not. Then, restricting the sample only on households reporting to have at least a non-farm entrepreneurship activity we performed a cluster analysis to find a categorization of households according to their similarity with respect to push or pull variables. Finally, we compute the probability of households to engage in the non-farm sector and we use this probability to control for self-selection and analyze food consumption and input adoption choice for households who diversify their income outside agriculture.

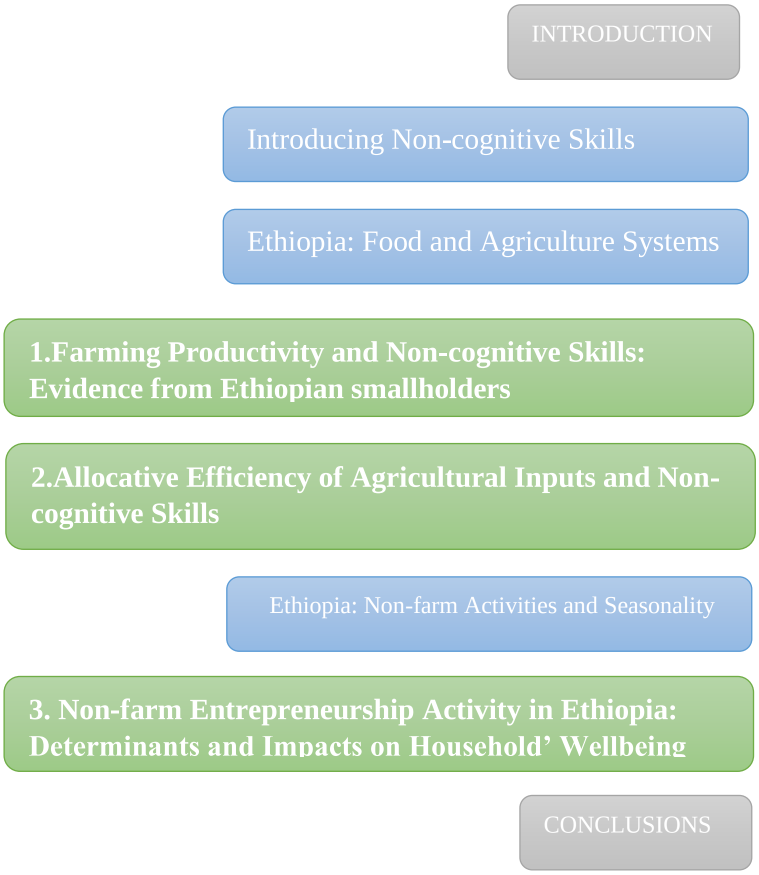
Structure of the Thesis

The thesis is structured as follows. The three main papers are presented in chapters 1, 2 and 3. **The first two papers** of the thesis share the same dataset and focus on Ethiopian farmers and their non-cognitive skills -in other words- the first research question mentioned. A brief chapter presenting non-cognitive skills' definition and the related economic literature (``Introducing Non-cognitive Skills''), and then exploring Ethiopian agricultural system and descriptive statistics (``Ethiopia: Food and Agriculture Systems'') precede the two papers. The first paper is called ``Farming Productivity and Non-cognitive Skills: Evidence from Ethiopian Smallholders'' and focuses on the estimation of agricultural output production function controlling for the personality traits of family members working on the plots. The second one ``The allocative efficiency of Agricultural Inputs and Non-cognitive Skills'' continues the analysis exploring the linkage between input equations and non-cognitive skills. Then it provides a weak validation of the recursivity strategy between input decisions and harvest outcome controlling for the non-cognitive skills endowment of farmers.

The third paper focuses on non-farm activities of Ethiopian smallholders and uses a different dataset compared to the previous chapters. The paper called ``Non-farm Entrepreneurship Activity in Ethiopia: Determinants and Impacts on Households' Wellbeing'' refers to the second research question presented. The paper is introduced by a brief description of the non-farm sector performance in Ethiopia during the last years and descriptive statistics for the dataset used for the subsequent empirical analysis (``Ethiopia: Non-farm Activities and Seasonality'').

Final considerations summarizing the results obtained within the thesis are presented in a concluding chapter.

Structure of the Thesis



The three main papers of the thesis are reported in the green frames. The blue rectangles refer to the introductory chapter presenting descriptive statistics and the background motivations before the empirical strategy of each paper. The grey boxes refer to general introductory and conclusive consideration of the dissertation.

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What are personality traits/non-cognitive skills?

Historically, there has been much considerable confusion around the concept of personality trait. Allport (1961) describes a trait as ``[…] a neuropsychic structure having the capacity to render many stimuli functionally equivalent, and to initiate and guide equivalent meaningfully consistent forms of adaptive and expressive behavior''. This definition influenced numerous subsequent definitions of personality traits. For example, Tellegen (1991) defined traits as ``a psychological organismic structure underlying a relatively enduring behavioral disposition, i.e., a tendency to respond in certain ways under certain circumstances''. But one can respond to a situation not only in ones behavior, but also with feeling and cognition. That is the reason why most personality psychologists agree that personality facets are ``enduring patterns of thoughts, feelings, and behaviors'' [Johnson, 1999] which, moreover, cannot dramatically change over short periods of time.

A distinction between personality and cognition is not easy to make. Non-cognitive skills or abilities are personality traits and are distinguished from intelligence, defined as the ability to solve abstract problems. Skills are not traits set in stone at birth and determined solely by genes: they can change with age and instruction [Heckman et al., 2014]. The definition of `skill' is not purely semantic: non-cognitive skills are capacities to function and they can be shaped over the life cycle. Families and social environments perform a powerful role in their formation. Like raw intelligence, non-cognitive skills are not determined solely by parental genes, although heritability plays an important role. Heritability studies show that measures of personality traits tend to be about 40%-60% heritable [Bouchard and Loehlin, 2001]. Heckman (2007) demonstrated that behaviors and abilities have both a genetic and an acquired character. Furthermore, biological sciences show there exist critical periods in skill development, the foundations of which are established in the early stages of childhood and through adolescence. As evidenced by Almond and Currie (2010), negative shocks in early childhood result in inferior outcomes later in life. In addition, skills are malleable at different stages of the life cycle: IQ scores become stable by age ten [Schuerger and Witt, 1989] while there is a wider margin for non-cognitive skills due to the malleability of the pre-frontal cortex into the early twenties [Dahl, 2004]. This region of the brains governs emotion and self-regulation. However, that evidence does not ask whether these changes occur naturally or whether they are due to changes in the environment.

Personality psychologists have taken advantage of the advances made in biology to provide an alternative model for the psychology of personality. This alternative perspective is called *Sociogenomics* [Robinson, Grozinger and Whitfield, 2005] and differs from standard biological personality psychology model proposed by Eynseck (1972 and 1997) where DNA represents the root of the system. This theory assumes that since genetic polymorphisms[4] do not change, then the influence on behavior must not change. While one of the key

[4] The term polymorphism was originally used to describe variations in shape and form that distinguish normal individuals within a species from each other. These days, geneticists use the term genetic polymorphisms to describe the inter-individual, functionally silent differences in DNA sequence that make each human genome unique [Weinberg,

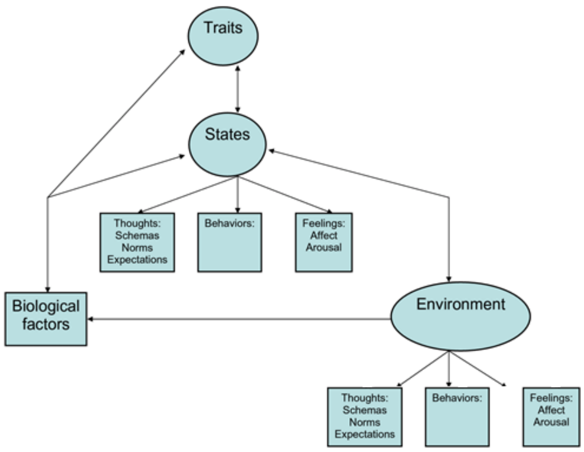
element of *sociogenomic* biology is the relation between biology and environment. We briefly describe a *sociogenomic* model in the next paragraph in order to present the context for the analysis of personality traits on households' outcomes.

-A Sociogenomic model of personality traits

We describe a sociogenomic model of personality traits to provide a link between personality traits and biological factors associated with personality. The model is derived from Roberts' (2009) paper and builds on state-trait models presented by Nezlek (2007), Steyer, Schmitt and Eid (1999). They first define *states* made up of enduring patterns of thoughts, feeling, and behaviors schemas, beliefs, chronically accessible constructs and moods. Second, *traits* are made up of stable enduring patterns of states which cause future state repetitions. The example provided by Roberts relates to a friend or a colleague who is habitually late at social engagements without feeling guilt (repetitive behavior and effect) leading one to conclude that he is not punctual. It is these repetitions in people's state profiles that are key to the inference that traits exist. People can act `out of the character' because of environmental influences, but usually, these do not cause long-term personality trait change because they affect short-term responses rather than radically and permanently change their traits. Behavioral inconsistency from moment to moment is to be expected and environmental influences help explain the shift in personality traits. However, if these state changes become persistent and extended, then they may cause changes in traits: personality change evolves into personality development. An example provided by Roberts (2009) could be students' opinions and actions in class that may lead some professors to change their approach to teaching and improving their classroom organization. Over the course of several semesters, the positive reaction of the students may bring a sense of work satisfaction and the belief the being organized is a good thing. Then, this belief could spread to other domains, since a reliable behavior pleases also other aspects of life. The environment could shape gradually and in a cumulative way the personality traits. Stressful states likely interact with genes responsive to stress, which in turn affect the neuroanatomy that shapes the habitual ability of the person to respond to future environmental stimulus.

This model offers the advantage of being amenable to experimental methods to demonstrate the causal role of traits. However, it is difficult to demonstrate causal effects on outcomes since it is challenging to manipulate traits and may also be unethical.

Figure 1 The sociogenomic model of personality traits (taken from Roberts, 2009)



2013].Genetic polymorphism is actively and steadily maintained in populations by natural selection, in contrast to transient polymorphisms where a form is progressively replaced by another [Begon, Townsend and Harper, 2006].

The Non-Cognitive Skills Literature in Economics

There is an ample empirical evidence showing that emotional factors affect individual decision-making in relation to their economic environment:

- Individuals focus on aspects of decision problems that are congruent with their emotional state [Bower and Cohen, 1982].
- Emotions affect the information that is retrieved from memory [Isen et al., 1978; Wright and Bower, 1992].
- Economic preferences are influenced by numeracy and intelligence. IQ test scores are determined not only by intelligence but also by factors as motivation and anxiety [Borghans et al., 2008].
- Emotion and soft skills may be important in explaining deviations of individuals from rational decision-making: the so called ``cognitive bias'' [Kahneman and Tversky, 1996].

The human capital literature has expanded over the past two decades to take into account non-cognitive abilities in order to give a more complete (or at least more psychologically credible) picture of *homo economicus*. These attempts include seminal **Heckman's works** [Heckman and Rubinstein, 2001; Heckman et al., 2006; Heckman and Kautz ,2012], which underline the strength of personality traits in predicting outcomes such as schooling, labor market, behavior and health. Heckman et al. (2006) show that the power of those personality traits that they consider equals or exceeds the predictive power of cognitive traits for those outcomes.

Heckman and Rubinstein (2001) use evidence from General Education Development (GED) testing program to demonstrate the quantitative importance of personality traits. Results show that GED recipients have the same cognitive ability as high school graduates who do not go to college. Nyhus and Pons (2005) have shown that emotional stability (an aspect of behavior connected with neuroticism) predicts higher wages. These results have important implications for policy-design: current systems of evaluation are based on scores on cognitive tests, but these results provide only a partial picture of skills required for a successful life since it is well-known that non-cognitive skills are traits most valued by employers[5]. In this sense, mentoring and motivational programs oriented towards disadvantaged teenagers are effective tools for increasing employability. Brunello and Schlotter (2011) reviewed a selected group of policy measures both in the US and in Europe that aim directly or indirectly at improving non-cognitive skill: evidence is somewhat mixed and scarce with some program more successful than others. Several countries already provide balanced assessment which incorporates non-cognitive skills in school curriculum at different education levels (see European Commission, 2010).

Following this approach, the World Bank *World Development Report* 2015 (WDR 2015) moves behavioral approaches to center stage, analyzing so-called ``small miracles". The WDR cites **Duflo's works** on nudging fertilizer use - the reason why farmers do not use fertilizer is in part because they procrastinate and postpone purchasing fertilizer until proceeds from the harvest are spent (Duflo, Kremer and Robinson, 2011) - and the power of reminders for ensuring timely access to HIV medical assistance administered in Kenya (Duflo, Dupas, Kremer and Sinei, 2006). Both papers demonstrate that the use of small precautionary measures (provision of moneyboxes to save money for purchasing fertilizers, and phone reminders for taking medications, respectively) results in significant improvement in outcomes - reduced procrastination and improve yield and health outcomes respectively.

Tognatta et al. (2016) focus on seven low and middle-income countries that participated in the STEP Skill Measurement Survey to conduct a comparative analysis of gender gaps. The concept is to use measures in order to capture different dimensions of human capital and to extend the literature on gender wage gap in developing countries. Using Blinder-Oaxaca decomposition results show that men receive a reward for scoring

[5] See Bowles and Gintis (1976), Edwards (1976) and Klein et al. (1991)

higher, on average, on openness and emotional stability traits. The interpretation is that men sort into occupations that require the appearance of more openness and emotional stability. Controlling for occupation, however, results do not confirm that sorting explains the entire difference between men's and women's returns to non-cognitive skills in Vietnam.

Fatalism is considered pervasive in many poor communities Bernard et al. (2012) investigates whether fatalistic beliefs have implications for the behavior of poor rural Ethiopian households towards investments in the future. Some researchers identify fatalism as a key factor explaining Ethiopia's slow socioeconomic transformation because people refrain from making investments that would enhance their wellbeing believing that these would not lead to significant changes. The key message is that the poor can and do make choices, and these choices may not coincide with those implied by standard economic reasoning.

Controlling for non-cognitive skills in analyzing farm production outcomes remains novel. Concerning productivity of dairy cows, the study of Hanna et al. (2009) shows no relationship between any Big Five Inventory traits of dairy stock farmers and milk yield in Northern Ireland. In most farms there was more than one person involved with the cows, this would have a confounding effect on the results reported. Having the possibility of relating psychological measures to successful stock farming it may prove possible to select employees with more appropriate psychological attributes or select those existing employees who would benefit most from training. In fact, farmers may be vulnerable to stress resulting from unpredictable weather or output prices. They are subject to time pressures, changes in government policies, and farm hazards. Many farmers are geographically isolated. Unanticipated events might generate psychological pressure [Willock et al., 1999].

Ali et al. (2017) provide another contribution in explaining farm production controlling for non-cognitive skills endowment of Ghanaian rice farmers. They proxy non-cognitive skills using 25 questions developed by industrial psychologists. They found three traits in particular -polychronicity, work centrality, and optimism- significantly affect simple adoption decisions, returns from adoption. Results from the stochastic frontier analysis show either technical efficiency in rice production is affected by non-cognitive skills. The study confirms the explanatory power of these traits exceeds that of traditional human capital measures.

In developing countries, women account for a large share of agricultural work performed on the farm. However, they generally have less access to land, agricultural extension program, credit and markets [Quisumbing and Pandolfelli, 2010]. Montalvao et al. (2017) document the psychological characteristics such as `strength of will' or `grit' of high-achieving women farmers in Malawi. A one standard deviation increase in female non-cognitive skills is associated with a 5.4 percentage point increase in tobacco adoption. The results are even stronger when controlling for patrilocal communities where women face greater adversity and the returns of these skills are the highest. All these considerations provide the motivation for including emotional and personality variables in agricultural production functions.

However, most of the evidence provided in existing studies are correlational: there is no strict proof that personality traits cause higher outcomes. Herrnstein and Murray (1994) present evidence on the correlation between levels of cognitive ability and different dimensions of social behavior, while Almlund et al. (2011) present association of the Big Five and intelligence with years of completed schooling. In the next section, we set out the theoretical framework developed by Heckman and Kautz (2012) which allows causal modeling of the role of emotions on agricultural yields.

An Economic Framework for Non-cognitive Skills

We set out the economic framework developed by Heckman and Kautz (2012) to interpret personality within an economic model. Suppose we have an indicator for performance on a task at age a, T_a, which depends on cognition C_a, personality P_a, other skills K_a and on the effort allocated to the task e_{T_a}:

$$T_a = \Phi_a(C_a, P_a, K_a, e_{T_a}), a = 1, \dots, A$$

Effort allocated to the task T_a again depends on cognition C_a, personality P_a other skills K_a, incentives R_{T_a}, and preferences Υ_a :

$$e_{T_a} = \psi_{T_a}(C_a, P_a, K_a, R_{T_a}, \Upsilon_a)$$

The effort applied to a task is the outcome of a choice problem that depends on traits, preferences, and incentives. Multiple traits, effort and acquired skills generate performance in a given task. To assume a linear relationship between outcomes and traits could be problematic since extreme levels of traits are associated with Obsessive Compulsive Disorder, which hinders task performance [Samuel and Widiger, 2008].

The traits and other acquired skills evolve over time through investment and habituation , I_a. Traits at age $a + 1$ are age dependent functions of cognitive ability, personality traits, other acquired skills and investment at age a. In this way, previous levels of traits and acquired skill affect current levels of traits and acquired skills.

$$(C_{a+1}, P_{a+1}, K_{a+1}) = \eta_a(C_a, P_a, K_a, I_a), a = 1, \dots, A$$

Measuring Non-cognitive Skills: BFI and ER tests

Achievement tests were developed to measure cognition during mid-twentieth century with the aim of evaluating individual performance. However, test scores predict only a small fraction of the variance in later-life success and neglect important dimensions of human potential. In order to capture those traits, psychologists have developed self-reported surveys based on self-reporting or indirect self-reports. The Big Five Inventory (BFI) and Emotion Regulation (ER) tests are the principal measurement systems for personality traits. They rely on taxonomies of traits established by psychologists and are based on self-report questionnaires. The BFI is among the most popular and most widely used tests [John and Srivastava, 1999]. Aggregating the different questions using the existing scale we obtain a score for each of the five traits. The BFI identifies five personality traits:

- *Conscientiousness* (organization skills and ability to act in a rational way). Individuals with high conscientiousness scores are often perceived as stubborn and obsessive while individuals with low conscientiousness scores are seen as flexible and spontaneous, but possibly also as sloppy and unreliable.
- *Agreeableness* (ability to cooperate in an unselfish way).
- *Extraversion* (energy, positive emotions, assertiveness, sociability and the tendency to seek stimulation in the company of others, and talkativeness).
- *Neuroticism* (the tendency to not control anxiety and stressful situations rationally). A low need for stability is seen to be associated with a reactive and excitable personality. Individuals who score highly on this test are often very dynamic, but can also be unstable or insecure.
- *Openness* to experience (tendency to be open to new circumstances and unfamiliar intellectual experiences).

The `Emotion Regulation' (**ER**) questionnaire summarizes the ability of an individual to dominate or control emotions or be affected by them (Gross and John, 1998, 2003). The ER test measures how subjects respond to stressful situations identifying two traits aggregating the score to each question:

- *Suppression* (defined as the ability to inhibit expressive behavior while emotionally aroused). Emotional suppression is negatively associated with mood repair and life satisfaction; positively with anxiety and self-esteem.
- *Reappraisal* (defined as the ability to interpreting potentially emotionally-relevant stimuli in unemotional terms). Individuals with a high reappraisal score are able to lower emotional intensity and hence improving function in circumstances in which individuals with high suppression scores might experience negative social consequences. Initial studies by Gross and John showed reappraisal to be related to greater positive affect, mood repair, life satisfaction, and reduced depression.

Several studies aimed to test the reliability and validity of these two psychometric tests we are using for our consequent analysis. The ER questionnaire has been widely used in studies of emotion regulation and the measures have demonstrated adequate to good internal consistency and temporal stability [Gross and John, 2003; Sala et al., 2012; Batistoni et al., 2013; Ioannidis and Siegling, 2015].

Schmitt et al. (2007) tested the assumption that the core psychological constructs transcend human language and culture, comparing scores of BFI for 56 countries. Since BFI (as well as ER) was developed in the U.S., any observed difference in mean scores between different culture may exist because of a real disparity on some personality trait, but also because of inappropriate translation, and biased sampling. Results show a lower congruence of BFI for Africa and Southeast Asia, especially for single items of the BFI Openness trait. Previous research failed to find a clear definition of openness in Black South African cultures.

Another related study is provided by Laajaj and Macours (2017) who test the reliability and validity of a wide set of non-cognitive skills measures -as well as BFI traits- among Western Kenyan farmers. This study represents one of the first structured attempt to validate technical and non-cognitive skills in a rural farming context in a developing country. A survey with a series of skills measurement was administrated to more than 900 farmers in Kenya. The reliability of the measures is attested with a second skill measurement after three weeks of the same questions asked included in the survey collected the first time. To test the predictive power of these measures in the survey were collected also information on agricultural practices and production. Results present mixed results on the ability of the tests to measure the intended skills in the sample considered. Some measurement challenges remain to be addressed to guarantee full reliability of such constructs. For instance, as Laajaj and Macours (2017) argue, in rural areas in developing countries the questions of the test are often read by an enumerator which could affect the responses. Nine percent of the variance of the non-cognitive skills can be explained by which enumerator posed the questions. In turns, the enumerator affects also the reliability of the measures quite substantially. Developing scripts to be followed literally can help training the enumerators. The low educational level of the respondents can affect the ability of the respondent to understand the question of the test This would lead to do not ignore the level of complexity introduced by the test. The order of sections is found to affect the measurement error too.

The general conclusion seems to be that only accounting for the main sources of measurement error can help increase the reliability and the predictive power of the non-cognitive skills test.

The contribution to the Behavioral discipline

Against this literature background, we want to stress the main contribution of this thesis to application of the behavioral approach in the context of developing countries. We can briefly summarize the main points as following:

- This work is one of the first attempt to introduce in a systematic way the impacts of non-cognitive skills on agricultural production and input adoption in a rural context in a developing country. Behavioral applications in developing are becoming common in the literature, but their implications for agricultural productivity remain unexplored despite the importance of agricultural sector in developing economies.

- Rural farmers are historically considered to be one of the most conservative sectors of the population in terms of their beliefs. In developing countries often households are trapped in agricultural activities because of the lack of off-farm alternatives. By introducing traits such organizational skills, reliability, enthusiasm and intellectual openness to new experience into the analysis, it is possible to shed new light on the motivation of the household's engagement in agriculture. Are peculiar traits, endurance and intellectual curiosity needed for success in farm activities under adverse conditions?
- In the empirical applications reported in this thesis, we only rely on constructs from a signle psychometric test. At the same time, we complement the BFI measures with the ER constructs to account for possible short-term deviations from the habitual individual behavior.
- The structure of the survey we emply allows us to use a detailed set of household and individual characteristics which we link to the personality traits measures
- We use a mix of qualitative and quantitative tools to measures this impact: we use descriptive statistics, statistical tests and Ordinary Least Square regressions to estimate the farm production function.
- The results we obtain generate a set of implications which may enable better targeting of input adoption policies. Some farmers may be more inclined than others to adapt to new agricultural technologies. Provision of limited incentives may foster a positive attitude towards innovation and improve the efficiency of input use on farms.

All these points will be addressed in a more extensive way in the following chapters.

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Background

Ethiopia is among the most populous countries in Sub-Saharan Africa, with a population of 97 million of which 80% live in rural areas (World Bank databank, 2016). Ethiopia has witnessed rapid economic growth, with real gross domestic product (GDP) growth averaging 10.9% between 2004 and 2014, which has lifted the country from being among the poorest in the world in 2000 to be in a position to become a middle-income country by 2025 provided it continues its current growth trajectory [World Bank, 2015]. Since 2000, households have experienced a decade of remarkable progress in well-being and the country has seen a 33% reduction in the share of the population living in poverty, only Uganda has had a higher annual poverty reduction during the same time period [World Bank, Ethiopia Poverty Assessment, 2014]. However, almost 30% of Ethiopians still live below the nationally defined poverty line and malnutrition is very widespread damaging over one-third of the total population [Ministry of Finance and Economic Development (MoFED), 2012; World Bank databank, 2016, respectively]. In addition, the country remains one of the poorest in the region, with a GDP per capita of only 486.3 constant 2010 USD$ in 2015, compared to Kenya (1,133.5 constant 2010 USD$), $) and Uganda (673.2 constant 2010 USD$) [see Table 1].

Table 1 GDP per capita in constant 2010 USD$

	2012	2013	2014	2015
Ethiopia	392	423	455	486
Kenya	1,043	1,074	1,101	1,134
Sudan	1,668	1,688	1,703	1,723
Uganda	653	653	662	673
Sub-Saharan Africa (excluding high income)	1,587	1,617	1,647	1,651

Created from: World Development Indicators Series: GDP per capita (constant 2010 US$)

Three new factors have been important over the period since 2013: a rapid expansion of community shops that supply inhabitants with necessary consumer items, the creation of `Ethiopian Grain Trade Enterprises' (EGTE) to help the volatility of food prices, and subsidization of fertilizers. Food price stability was achieved in 2014 thanks to the recent decline in global prices of food and fuel coupled with state intervention. The great institutional efforts at a federal and local level such as the implementation of safety nets and price control measures brought some results, but farmers still struggle owing to high fertilizer prices and the timing of tax and debt payments.

As a result of the impact of the 2015 drought, on crop production and food security conditions have sharply deteriorated since mid-2015, with the estimated number of food-insecure people increasing from 4.5 million in August to 10.2 million during the first semester of 2016 [FAO GIEWS Country Brief: Ethiopia, 2016]. In addition, the very poorest in Ethiopia have become even poorer: the high food prices that improve incomes for many poor farmers make buying food more challenging for the poorest [World Bank Press Release on Poverty

Assessment, 2015]. Furthermore, Ethiopia is one amongst the largest refugee-hosting country in Africa, with about 738,000 refugees and asylum seekers from South Sudan, Somalia, Eritrea and the Sudan. The fragile ecosystem and scarcity of resources have led to tensions between host communities and refugees in some locations [FAO GIEWS Country Brief: Ethiopia, 2016].

- *The Food and Agriculture Sector in Ethiopia*

Agriculture dominates economic activity and accounts for a much larger share of GDP in Ethiopia (41.0%) than in neighboring Kenya (32.9%), Sudan (28.6%) or Uganda (24.7%) [World Bank data, 2015]. In addition, it is mostly characterized by subsistence farming, heavily dependent on weather variations and seasonal variability[6].

More than 70% of the cultivated land is under cereals (maize, teff, barley, wheat, and sorghum) that are mostly used for household consumption.

Teff is an indigenous crop cultivated at great altitudes and is the major staple food in Ethiopia, accounting for 28% of all cultivated land. It is noted for its high quality and high yield and it is the main ingredient for preparing *enjera*, a sourdough-risen flatbread. Maize is the second most cultivated cereal in Ethiopia in terms of area, although is less tolerant of cold than teff, barley and wheat. Sorghum cultivation, which accounts for 17% of cultivated land, adapts to a variety of extreme conditions: in fact, it is drought tolerant, it can accept excess of water conditions, and it grows best in semiarid conditions. However, is sensitive to cold and high altitudes. Coffee, cultivated in the rainfall sufficient southern highlands is Ethiopia's major export crop. While livestock is the major sources of meat and livelihood of the pastoralist populations.

We can conclude that Ethiopia's rural poverty could be likely be the result of land shortages in the high-land, low food productivity, recurrent droughts and variable rainfall. Since Ethiopia's crop agriculture continues to be dominated by smallholders and with little suitable land available for the expansion of crop cultivation, future cereal production growth will need to come from yield improvements such as those resulting from improved seeds and greater application of inorganic fertilizers.

- *Smallholder Technology Adoption*

The country faces major strategic questions regarding the role of agriculture in its overall economic development plan. The relative stagnation of cereal yields suggested to many that significant expansion of smallholder production is constrained by land shortage in Ethiopian highlands, limited potential for irrigation, inadequate infrastructure and a weak seed sector [Dorosh and Rashid, 2012].

Table 2 reports statistics for agricultural technology adoption indicators in Africa for available countries (Niger, Tanzania, Malawi, Nigeria, Uganda and Ethiopia) and time of collection (2010 or 2011). Ethiopia shows the highest percentages for improved seed varieties, irrigation and organic fertilizer usage; while for the adoption of agro-chemicals and inorganic fertilizers is surpassed by Nigeria and Malawi, respectively.

[6] However, following Gilbert et al. (2016) results Ethiopia's seasonal gap for main staple cereals -the difference between the high price immediately prior to the harvest and the low price following the harvest averaged across 10 years- is one of the lowest amongst other African countries such as Niger, Burkina Faso, Malawi and Ghana which show an average seasonal gap in excess of 30% at wholesale level. While Tanzania and Uganda are intermediate at around 25%.

Table 2 Agriculture in Africa – Technology adoption indicators

	Niger (2010)	Tanzania (2010)	Malawi (2010)	Nigeria (2010)	Uganda (2010)	Ethiopia (2011)
Female share of agricultural labor by agricultural activities(All)	24.0	53.0	52.0	37.0	56.0	29.0
Percent of cultivating households using modern inputs (agro-chemicals)	8.0	13.0	3.0	33.0	11.0	31.0
Percent of cultivating households using modern inputs (improved seed varieties)	3.0	NA	NA	NA	NA	24.0
Percent of cultivating households using modern inputs (inorganic fertilizer)	17.0	17.0	77.0	41.0	3.0	56.0
Percent of cultivating households using modern inputs (irrigation)	7.0	4.0	1.0	4.0	4.0	9.0
Percent of cultivating households using modern inputs (mechanized inputs)	NA	NA	NA	47.0	NA	NA
Percent of cultivating households using modern inputs (organic fertilizer)	55.0	20.0	18.0	3.0	13.0	66.0

Source Project: Agriculture in Africa – Telling Facts from Myths, World Bank databank
NA: the data is not available for the indicator and the year

Over the past two decades, decision-makers in Ethiopia have pursued a range of policies and investments to boost agricultural production and productivity. The government of Ethiopia launched a strategy known as `Agricultural Development Led Industrialization' (ADLI) in 1993, one of the major component is the national extension package program known as `Participatory Demonstration and Training Extension System' (PADETS). The objective of this program was to increase farm productivity through enhanced supply and promotion of improved seeds, fertilizers, on-farm demonstrations of improved farm practices. The impacts of the program were mixed with the increased use of fertilizer but poor productivity growth [World Bank, 2006].

The literature has shown that constraints to agricultural technology adoption decision are explained by imperfect information, risk, uncertainty, institutional constraints, human capital, input availability and infrastructural problems Yanggen et al. (1998) showed that in Africa fertilizer use capacity is constrained by a prevalent lack of human capital (basic education, extension and health/nutrition), financial capital (income, credit and assets) and basic services (infrastructure, quality controls and contract enforcement, information and government policies). Yield response factors (biophysical environment, technology and extension) and high input prices combined with low output prices (structure conduct and performance of subsector, competition efficiency and equity) have also contributed.

It seems possible that non-cognitive skills may also play a role in determining the decision to adopt new technology in agriculture. Motivation, optimism, and sociability may also be important determinants of smallholders' decision to buy and apply inorganic fertilizer or to trust extension advice. This issue is addressed in the following sections.

- *Land Tenure Policy*

Households living in rural areas and involved in the agriculture sector consider land as their main asset: it serves as a store of wealth against inflation, as the source of self-employment and food security, as collateral for credit, and as a source of insurance. Access to land is therefore of fundamental importance

Land tenure policies have changed dramatically over time in Ethiopia. The current government policy is based on state ownership that ensures free access to land for all people of Ethiopia in order to prevent a small number of wealthier landowners from acquiring a majority of the land. This legislation was designed to protect against conditions experienced under the imperial regime, where a majority of rural farmers worked under tenancy contracts with exploitative labor agreements [Jemma, 2001; Rahmato, 2004; Chamberlin and Schmidt, 2009].

The most recent proclamation dates back to 2005 when the central government issued a revised proclamation designed to increase subjective tenure security through land registration and certification of plots while remaining within the context of the state-owned land law. The result is that rural households can use the land for agriculture production, have full ownership of the products from their farming, have right to rent to fellow farmers, lease to investors, and inherit and donate to family members. The right of sale and mortgage are not included, but holding rights give farmers sufficient tenure security to make land investments [Scandizzo, Savastano and Alfani, 2012]. These rights may and also possible `psychological relief' which will be the subject for our subsequent analysis. However, concerns have been raised that state ownership and limits to land transfers are restricting the development of key land markets, producing negative spillovers in agricultural productivity and off-farm labor (EEA/EEPRI 2002; Deininger et al. 2004).

Data

The Centre for the Study of African Economics (CSAE), in collaboration with the International Food Policy Research Institute (IFPRI), has collected a unique panel data set Ethiopia Rural Household Survey (ERHS) covering household in a number of villages in rural Ethiopia from the late 80s until 2009. The 2012 round is a stand-alone survey with household sampled from ERHS panel data, the survey was financed by FAO and implemented by the University of Addis Ababa in collaboration with Centre for Economic and International Studies (CEIS) of University of Rome TorVergata. The ERHS covered all regional states except the capital, Addis Ababa. It primarily collected information on rural areas. It was implemented in 290 rural and 43 small town enumeration areas (EAs). The 2012 round covers 501 households mostly living in the Oromia region (55% of households) with the remaining household living in the Amhara region. The survey consists of three rounds of visits to the household. The first round was carried out in September and October 2011 and collected information on post-planting agriculture activities. The second round was conducted in November-December 2011 and fielded the livestock questionnaire to collect information on ownership, production and utilization of livestock, and livestock by products. The third round took place in January-March 2012 to collect information included in the post-harvest agriculture, household, and community questionnaires[7].

The survey includes field production information on about 1400 parcels of land (size of parcels, yield, labor and agricultural input usage, and information on soil quality) together with demographic and other household information (age, gender, education level, distance from the cultivated plot, wealth index). Furthermore, respondents compiled a section of the survey which allowed the construction of BFI and ER indices, to derive measures for non-cognitive skills (`the scores') to be used in the subsequent analysis.

Due to the small sample size (501 households interviewed) and the high compliance to input usage on farm (presented later in the main descriptive statistics) we believe that exist a sampling bias. The main consequence is that empirical results would not have external validity and will not be representative for entire rural Ethiopia.

- <u>*Descriptive statistics*</u>

In this paragraph, we present the main descriptive statistics for the sample focusing on the relationship between agricultural variables, cognitive abilities and non-cognitive skills. The principal descriptive statistics are shown in Table 3. The average size of the parcel is 0.56 hectares (with a standard deviation of 0.51, and a median of 0.50 hectares), while household total crop area id 2.07 hectares (with a standard deviation of 1.30, and a median of 1.75 hectares). Households cultivate, in average, 1.5 different types of crops on each plot – the range goes from a minimum of a 1 to a maximum of 9 different crops-. 83% of plots have a formal certificate of acquisition.

The most frequently cultivated crops in the sample are the white teff variety (on average 0.56 hectares are allocated to its cultivation, with a yield of 109.31 Kg/ha, wheat 0.41 hectares with a yield 88.87 Kg/ha and maize 0.38 hectares, with an average yield of 75.28 Kg/ha. Data on quantity harvested and crop area was

[7] It was not possible to recover other detailed information about the sampling design

imputed for regions and woreda levels[8]: namely, we replaced outliers with median values stratified by region and woreda levels. Female-headed households are less than 30% of the sample. Average household education level is almost 4.4 years of schooling, on average 70% of households' heads have no education at all. Household size average is 5.75.

We use a proxy for agricultural productivity a multi-crop index following Owens et al. (2003), Liu (2006) and Peterman et al. (2011). The multi-crop output K_i is a measure of value of crop yield per area unit calculated as quantity produced for each crop per hectare (y_{ik}) multiplied by caloric intake of that specific crop (c_k).

$$K_i = \sum_i (y_{ik} c_k)$$

As a robustness check, we use an alternative multi-crop measure in which output is weighted by unit prices[9] (p_k).

$$Y_i = \sum_i (y_{ik} p_k)$$

Table 3 Descriptive Stats

	Obs	Average	Std Dev
HH Characteristics			
Female HH Head	501	0.28	0.45
HH Size	501	5.75	2.65
No HH Head Education (=1)	501	69.81	0.49
Age (years)	501	28.76	12.63
Gross Agr. Inc (Crop+livestock) (BIRR)	501	8,857.64	14002
Gross Aggregate Inc (BIRR)	501	11,135.13	14919
HH member migrant (=1)	501	0.68	0.46
Credit (at least 100 Birr) (=1)	501	0.37	0.48
Agricultural Variables			
Distance from Plot (minute)	1481	27.88	34.72
Crop Area (ha)	1465	2.073	1.3
Dummy for Monoculture (=1)	1481	0.69	0.46
Dummy for Low Quality Soil (=1)	1480	0.127	0.33
Dummy for Normal Quality Soil (=1)	1480	0.5	0.5
Total Yield (KG/ha)	1481	101.64	135.58
Multicrop Output (KG/BIRR)	1481	987.29	4622.56
Cultivation by Hand (=1)	1481	0.16	0.37
Cultivation with Animal (=1)	1481	0.84	0.37

Table 4a shows the share of plots adopting agricultural inputs such as hybrid seeds (87%), inorganic fertilizers (86%), pesticides (23%) and use of an irrigation system (99%). These high percentages make us believe the existence of possible sampling bias. The main consequence is that empirical results would not have external validity and will not be representative for entire rural Ethiopia. We provide to compare the basic descriptive statistics of ERHS data which covers households in a number of villages in rural Ethiopia from the late 1980s until 2009. From ERHS panel data structure was sampled the 2012 round we use in the analysis. In 2009, 23% of households in the sample used hybrid seeds; 50% used inorganic fertilizers, 20% acquired pesticides, and 24% used some irrigation on one or more plots (Table 4b).

[8] Woredas are the third-level administrative divisions of Ethiopia; woredas are aggregated into zones to create regions.
[9] Unit prices were calculated for each household by dividing total sales values by the quantity sold, where a household did not sell any of the crop, its total yield is multiplied by the median price received by farmers in that specific location. We use unit price instead of state-market prices as Owens et al. (2003) for Zimbabwe, even though the possibility of edongeneity of unit prices deriving from farmer characteristics.

Table 4a Agriculture Input Adoption

Variable	N	Mean	Std. Dev
Hybrid Seed	501	0.87	0.33
Inorganic Fertilizer	453	0.86	0.34
Pesticides	501	0.23	0.418
Irrigation System	501	0.99	0.100

Table 4b Descriptive Statistics from `Ethiopian Rural Household Survey' longitudinal data. 2012 survey is a stand-alone survey with household sampled from ERHS panel data

	Mean				
	Female-Headed Household	HH size	No HH Head Education (=1)	HH Head Age	Tot Crop Area (ha)
2009	0.3196126	5.713479	0.4898457	52.93664	1.480888
2004	0.2800646	5.748184	0.582716	51.0223	1.426379
1999	0.2631154	5.881356	0.6089069	49.48664	1.755847
1994	0.196933	6.299435	0.7252836	46.15653	1.773703

Agr Inputs

Dummy for having used fertilizer	Mean	Dummy for HH using improved seeds	Mean	Dummy for HH acquired pesticides (incl. Fungicides and herbicides)	Mean	Dummy for some irrigation on one or more plots	Mean
2009	0.50	**2009**	0.23	**2009**	0.20	**2009**	0.24
2008	0.54	**1999**	0.14	**2004**	0.01	**2004**	0.23
2007	0.54			**1999**	0.21	**1999**	0.10
2006	0.55						
2005	0.55						

Data Source: `Ethiopian Rural Household Survey' longitudinal data, collected by IFPRI

- *Non-Cognitive Skills Measures*

We now turn to the BFI and ER scores. Non-cognitive skills are collected at the individual level and so are the descriptive statistics on these variables. Responses to all 44 BFI questions are on a scale of one to five, with five indicating ``agree strongly'' and one indicating ``disagree strongly''. While, responses to all 10 questions or ER test are on a scale of one to seven, with seven indicating ``agree strongly'' and one indicating ``disagree strongly''. Each measure of the two tests is created aggregating the different questions using the existing scale and taking the simple average of items that belong to that specific domain (see the Appendix I). Each score was converted into T- scores: having a range between 20 and 80[10].

The five traits defined by the test correspond to *agreeableness*, *conscientiousness*, *neuroticism*, *extraversion*, and *openness* to experience. We derive two further personality traits from ER questionnaire. These concern the respondent's abilities to control emotions and how these affect decision-making: *reappraisal* and *suppression*.

We report Cronbach's alpha[11] as a measure of the internal reliability of BFI and ER scores in Table 5: values of alpha increase as the correlations among test items increase (average reliability is 0.67 which indicates almost reliable consistency, where the rule of thumb is to around 0.7). Although results are in line with the existent literature on BFI scores in Africa[12], low internal reliability might due to language and culture differences. The test scale for ER test is 0.58.

[10] In the following chapters we may refer to these measures using the denomination `score' or `T-score' as synonym

[11] Cronbach's alpha is used as a lower bound estimate of the reliability of a psychometric test. Suppose that we measure a quantity which is a sum of K components, Cronbach's alpha is defined as $\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right)$ where σ_X^2 is the variance of the observed total test scores, and $\sigma_{Y_i}^2$ the variance of the component i for the current sample of persons. Rule of thumb to have a reliable psychometric indicator is 0.70

[12] See Schmitt et al. (2007). In this paper is tested the assumption that the core psychological constructs transcend human language and culture, comparing scores of BFI for 56 countries. Since BFI was developed in the U.S., any observed difference in mean scores between different cultures may exist because of a real disparity on some personality trait,

However, Laajaj and Macours (2017) argued that the Cronbach alpha is affected both by the noise and the extent to which items are measuring the same underlying construct. Measurement errors could be generated by several sources amongst which areinterviewer characteristics, low level of education, the order of the section of the survey and other cognitive biases. Laajaj and Macours try different methods for aggregating responses. For example, they account for the tendency of the respond to agree with the statement presented in the questions, correcting for latent factors with exploratory factor analysis (EFA) and Item Response Theory. Unfortunately in our case, we cannot control *ex-post* for these sources of measurement error since the original survey design did not include controls for measurement errors in relation to non-cognitve skills (as well as the cognitive ones). In our case, we simply rely on the Cronbach alpha aware of the possible limitations of this statistical tool. However, we try to check for other statistical correlation between the results of the two tests' scores and other variables to identify a possible latent relationship between the two.

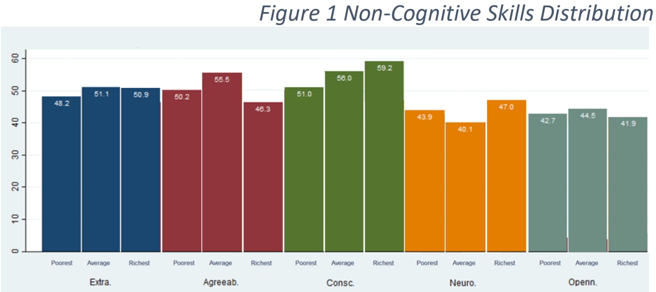
Table 5 Descriptive Statistics and Cronbach's alpha

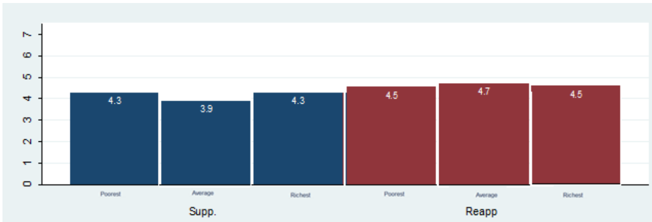
BFI	Mean	Std Dev	Min	Max	Alpha
Extraversion T-score	50.93	6.07	35	70.71	0.68
Agreeableness T-score	55.33	9.13	24.17	70	0.59
Conscientiousness T-score	56.34	6.7	34.73	70	0.57
Neuroticism T-score	40.61	6.71	26.07	60.71	0.58
Openness T-score	44.41	6.89	27.71	62.86	0.66
Test Scale					0.67
ER Test Sale					0.58

The theoretical value of alpha varies from 0 to 1. The last column gives Cronbach's α for the test scale, which consists of all but the one item. A commonly accepted rule for describing internal consistency using Cronbach's Alpha is to have a test scale around 0.70

Figure 1 shows the distribution of BFI and ER scores for household perceptions as to whether they are among the poorest, towards the average or among the the richest in their village (information collected directly with the questionnaire). We are not in a position to make an assumption on the direction of causality - whether poverty affects non-cognitive skills endowment or being poor is caused directly by personality traits. We notice that those households who perceived themselves as poorer show on average higher scores in Agreeableness and Openness whilericher households have on average higher scores in Conscientiousness and Neuroticism.

Figure 1 Non-Cognitive Skills Distribution by Household Perception of Wellbeing





We exclude the possibility of multicollinearity issues for the following econometric estimations by looking at the correlation between schooling, wealth and non-cognitive skills [Table 6]. The small number of people in rural regions who have obtained some level of schooling may have personality traits that differ from the other sampled individuals, and moreover, the schooling process could strengthen such abilities. Thus, the information of BFI and ERmeasures are largely orthogonal to education and experience. Then we test whether

but also because of inappropriate translation, biased sampling. Results, show a lower congruence of BFI scores for Africa and Southeast Asia, especially for single items of the BFI Openness trait (as in out sample). Previous research failed to find a clear definition of openness in Black South African cultures. Furthermore, it would seem logical to expect that the economic prosperity of a nation would be related to the conscientiousness of its citizens or at least that conscientiousness would be a favorable factor for economic development. Contrary to this expectation, the correlation between the BFI factor scores of Conscientiousness and gross domestic product (GDP) per capita approached marginal significance in the negative direction.

individuals with some level of education statistically differ in non-cognitive skills endowment respect to people without any schooling attainment. Results show that on average people able to afford education have higher non-cognitive skills scores (except for Neuroticism trait). On average individuals with basic education have 2 points more for the conscientiousness and 3 points for the openness traits [Table 7].

Even though we already graphically represented the relationship between own-perception of the wealth status of households we check also a possible correlation with the derived measures of wealth and income. In this case, we notice that behavioral variables are largely uncorrelated with wealth measures (Gross aggregated income, number of assets owned).

Table 6 Correlation tables

	Output Index	Schooling (yeas)	HH Head Age (years)	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Suppression	Reappraisal
Output Index	1.0000									
Schooling (yeas)	-0.0061	1.0000								
HH Head Age (years)	-0.0019	0.0679	1.0000							
Extraversion	0.0818	-0.0475	-0.0227	1.0000						
Agreeableness	0.036	0.0101	0.0163	0.2495	1.0000					
Conscientiousness	0.006	0.1162	-0.0758	0.0554	0.3575	1.0000				
Neuroticism	0.0081	-0.099	0.0516	0.0602	-0.4308	-0.5619	1.0000			
Openness	0.0866	0.1811	-0.0121	0.3142	0.1135	0.4303	-0.2943	1.0000		
Suppression	-0.0058	0.0009	-0.0626	-0.1915	-0.0962	0.1568	-0.0739	0.126	1.0000	
Reappraisal	0.0137	0.0281	-0.0104	0.136	0.1512	0.3184	-0.2403	0.3296	0.4455	1.0000

	Gross Aggr Income	Number of Bikes	Number of Cell	Number of Radio	Agreeableness	Extraversion	Conscientiousness	Neuroticism	Openness
Gross Aggr Income	1.0000								
Number of Bikes	0.0566	1.0000							
Number of Cell	0.2539	0.2795	1.0000						
Number of Radio	0.1991	0.1903	0.2365	1.0000					
Agreeableness	0.2058	-0.0712	0.0171	0.0418	1.0000				
Extraversion	0.0364	-0.0951	0.0135	0.0045	0.2994	1.0000			
Conscientiousness	0.2115	-0.0659	-0.0745	0.0329	0.3804	0.1173	1.0000		
Neuroticism	-0.2807	-0.004	-0.0501	-0.0942	-0.4904	0.058	-0.5327	1.0000	
Openness	0.1205	0.0116	0.0833	0.0364	0.0459	0.3972	0.3372	-0.1806	1.0000

We use Gross aggregate income and number of bikes, cellphones and radios to proxy household wealth. BFI Scores refers to Family members working on the plot

Table 7 T-test BFI and ER score for people with/without educational attainment

BFI Scores	**Mean (No Education)**	**Mean (Education>1 year)**	**Difference**
Extraversion	50.591	51.067	-.477*
Agreeableness	53.904	54.529	-.625*
Conscientiousness	53.750	56.028	-2.27***
Neuroticism	42.516	40.554	1.962***
Openess	41.781	45.192	-3.412***
ER Scores			
Suppression	3.997	3.998	-.001
Reappraisal	4.634	4.744	-0.110***

Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1

We test whether land tenure security affects household personality traits. Table 8 reports the t-test statistics for BFI and ER. We can assume that having a plot certificate is an exogenous outcome for households and also that having a certificate could decrease psychological distress and increases subjective psychological wellbeing. This could favorably affect the land investment and subsequent farming productivity. Results confirm that respondents in households without formal plot certificates show on average higher neuroticism while members living in households with a certificate are more open to new experience and show higher scores for suppression.

Table 8 T-test BFI and ER score for plots with/without formal certificate

Variable	Mean (No Plot Certificate)	Mean (Plot Certificate)	Mean Total	Diff
BFI Scores				
Extraversion	50.48	51.03	50.93658	-0.55
Agreeableness	55.61	55.28	55.34	-0.33
Conscientiousness	55.94	56.17	56.14	-0.24
Neuroticism	41.66	40.40	40.61	1.26***
Openness	43.64	44.57	44.41	-0.93*
ER Scores				
Suppression	3.75	3.99	3.95	-0.23***
Reappraisal	4.71	4.76	4.75	-0.04

Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1

We test whether cognitive and non-cognitive skills of family members working on the plot differ between who adopt a certain level of agricultural inputs. In Table 9 we report results for t-test between the users and non-users of inorganic fertilizer (first three columns) and between the users of low quantities of seeds (first and second terciles of the distribution) and intensive users (third tercile). The results show that non-cognitive skills differ across these groups. In particular, family members who apply inorganic fertilizer on the plot show on average higher scores for extraversion and agreeableness (0.88 and 1.25 points respectively), and lower scores for conscientiousness (-0.77 points). The results for the t-test on seed purchase are more difficult to interpret since households may choose to purchase high-quality seed to enhance output or may be obliged to purchase seed because of insufficient retention from the previous crop year. These two possible categories of seed purchaser are likely to be associated with different behavioral traits. The t-test results show a statistically significant difference in household average educational attainment used to proxy cognitive skill. Individuals who apply lower quantities of seeds have on average a half-year more of education compared to people who apply larger quantity. As with the results for inorganic fertilizer adoption, family members who apply a larger quantity of seeds on the plot show on average higher scores for extraversion, agreeableness and suppression, and lower scores for conscientiousness.

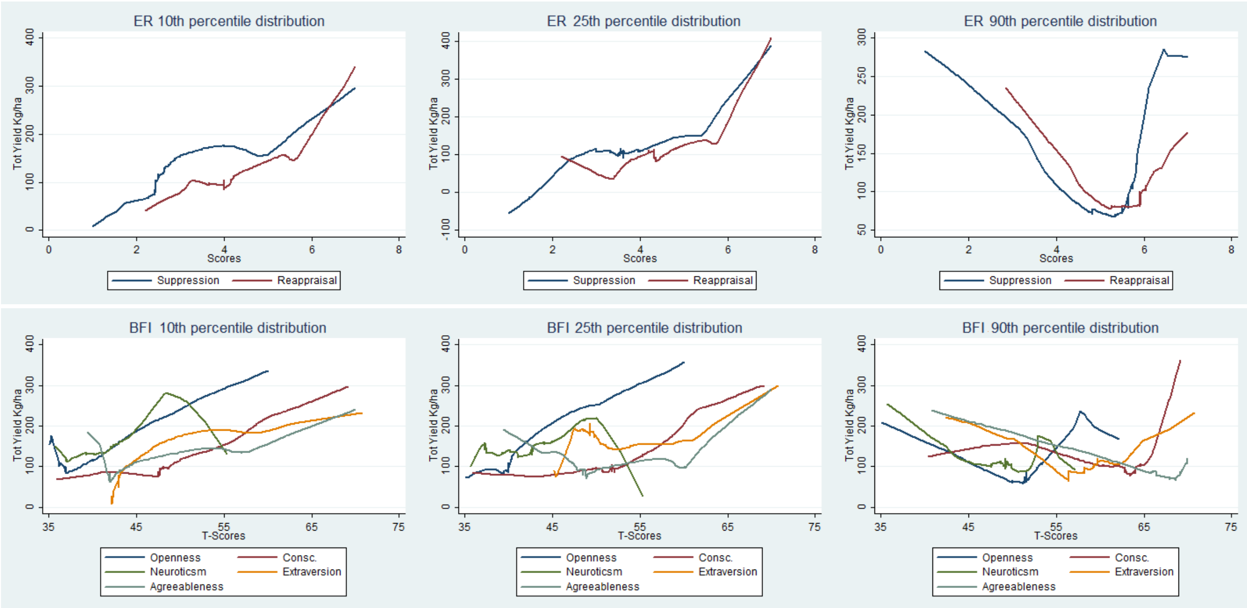
Table 9 T-test BFI and ER score for family members working on the plot by technological adoption

	Mean **(No Inorg Fert)**	Mean **(Some Inorg Fert)**	**Difference**	Mean **(1st, 2nd terciles of quantity of seeds applied per ha)**	Mean **(3rd tercile of quantity of seeds applied per ha)**	**Difference**
Cognitive Skill						
Household Average Educational Attain.	3.66	3.85	-0.19	3.87	3.59	.51***
BFI Scores						
Extraversion	50.33	51.21	-.88**	50.63	52.15	-1.51***
Agreeableness	54.41	55.67	-1.25**	55.02	56.23	-1.21*
Conscientiousness	57.08	56.81	.77*	57.04	55.55	1.85***
Neuroticism	40.59	40.53	0.06	40.47	40.93	-.46
Openess	44.53	44.7	-0.17	44.6	44.82	-.21
ER Scores						
Suppression	3.93	3.98	-0.05	3.92	4.17	-.26**
Reappraisal	4.81	4.72	0.09	4.75	4.77	-.02

Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1

We explore the relationship between BFI and agricultural productivity measures (total crop yield under all crops Kg/ha) plotting the yield against the quantile distribution of BFI and ER scores in Figure 2. The graphs show a common pattern: top quantile distribution of BFI and ER show a decreasing trend in scores as total yield increases, while the reverse is true at the bottom of the distribution.

Figure 2: Quantile Distribution of BFI and ER on Total Yield (Kg/ha)



In this section, we provided a descriptive picture of the possible connection between non-cognitive skills and farming system of rural households in Ethiopia. For instance, there are several interesting hints to further explore the contribution of non-cognitive skills on the wellbeing of rural households. We are aware of the possible limitations of our approach, especially the threat of measurement errors that could hinder the goodness of our non-cognitive skills measures. Laajaj and Macours (2017) are rather skeptical on the use of these measures because often they do not measure what they supposed to. On the other hand, thereis other more positive evidence such as: Ali et al. (2017), Montalvao et al. (2017), and Bernard et al. (2012).

After this exploratory and mainly correlational analysis in the next chapter, we try to assess in a more rigorous way the impacts of such skills on agricultural output performance.

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APPENDIX I

Big Five Questionnaire

Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
1	**2**	**3**	**4**	**5**

1----------------------------------2----------------------------------3-------------------------------------4----------------------------------5

___ 1. is talkative
___ 2. tends to find fault with others
___ 3. does a thorough job
___ 4. is depressed, blue
___ 5. is original, comes up with new ideas
___ 6. is reserved
___ 7. is helpful and unselfish with others
___ 8. can be somewhat careless
___ 9. is relaxed, handles stress well
___ 10. is curious about many different things
___ 11. is full of energy
___ 12. starts quarrels with others
___ 13. is a reliable worker
___ 14. can be tense
___ 15. is ingenious, a deep thinker
___ 16. generates a lot of enthusiasm
___ 17. has a forgiving nature
___ 18. tends to be disorganized
___ 19. worries a lot
___ 20. has an active imagination
___ 21. tends to be quiet
___ 22. is generally trusting
___ 23. tends to be lazy
___ 24. is emotionally stable, not easily upset
___ 25. is inventive
___ 26. has an assertive personality
___ 27. can be cold and aloof
___ 28. perseveres until the task is finished
___ 29. can be moody
___ 30. values artistic, aesthetic experiences
___ 31. is sometimes shy, inhibited
___ 32. is considerate and kind to almost everyone
___ 33. does things efficiently
___ 34. remains calm in tense situations
___ 35. prefers work that is routine
___ 36. is outgoing, sociable
___ 37. is sometimes rude to others
___ 38. makes plans and follows through with them
___ 39. gets nervous easily
___ 40. likes to reflect, play with ideas
___ 41. has few artistic interests
___ 42. likes to cooperate with others
___ 43. is easily distracted
___ 44. is sophisticated in art, music, or literature

Big Five Inventory Scoring Key [13]

Extraversion:	1, 6R [14],11, 16, 21R, 26, 31R, 3	Neuroticism:	4, 9R, 14, 19, 24R, 29, 34R, 39
Agreeableness:	2R, 7, 12R, 17, 22, 27R, 32, 37R, 42	Openness:	5, 10, 15, 20, 25, 30, 35R, 40, 41R, 44
Conscientiousness:	3, 8R, 13, 18R, 23R, 28, 33, 38, 43R		

Total Scores Converted to T-Scores

Extraversion___. Total Score divided by 8 = ____ (X). X minus 3.2 = ____ (Y). Y divided by 0.8 = (Z) = ____. (Z * 10) + 50 = ____ (T)

Agreeableness___. Total Score divided by 9 = ____ (X). X minus 3.8 = ____ (Y). Y divided by 0.6 = (Z) = ____. (Z * 10) + 50 = ____ (T)

Conscientiousness___. Total Score divided by 9 = ____ (X). X minus 3.6 = ____ (Y). Y divided by 0.7 = (Z) = ____. (Z * 10) + 50 = ____ (T)

Neuroticism___. Total Score divided by 8 = ____ (X). X minus 3.0 = ____ (Y). Y divided by 0.8 = (Z) = ____. (Z * 10) + 50 = ____ (T)

Openness___. Total Score divided by 10 = ____ (X). X minus 3.7 = ____ (Y). Y divided by 0.7 = (Z) = ____. (Z * 10) + 50 = ____ (T)

[14] Note that "R" denotes reverse-scored items (1=5, 2=4, 3=3, 4=2, 5=1).

Emotion Regulation Questionnaire

Disagree strongly	Neither agree nor disagree	Agree strongly

1----------------------2---------------------3---------------------------4---------------------------5---------------------6---------------------7

---

1. ____ When I want to feel more *positive* emotion (such as joy or amusement), I *change what I'm thinking about*.
2. ____ I keep my emotions to myself.
3. ____ When I want to feel less *negative* emotion (such as sadness or anger), I *change what I'm thinking about*.
4. ____ When I am feeling *positive* emotions, I am careful not to express them.
5. ____ When I'm faced with a stressful situation, I make myself *think about it* in a way that helps me stay calm.
6. ____ I control my emotions by *not expressing them*.
7. ____ When I want to feel more *positive* emotion, I *change the way I'm thinking* about the situation.
8. ____ I control my emotions by *changing the way I think* about the situation I'm in.
9. ____ When I am feeling *negative* emotions, I make sure not to express them.
10. ____ When I want to feel less *negative* emotion, I *change the way I'm thinking* about the situation.

Reappraisal: 1, 3, 5, 7, 8, 10; Suppression: 2, 4, 6, 9

1.Farming Productivity and Non-cognitive Skills: Evidence from Ethiopian Smallholders

1.1. Introduction

The use of behavioral approach in the economic discipline has blooming during the last years. The motivation for including emotions and personality traits is to try to give a more complete picture of *homo economicus*. Heckman's works testify the strength of the behavioral variables in predicting outcomes in schooling, labor market behavior and health. The success of this approach is confirmed by its spreading in developing countries too. The World Bank's 2015 *World Development Report* (WDR 2015) collects the best examples of behavioral application in developing countries referring to them as `small miracles' (amongst the which the WDR cites Duflo's works on the power of nudging fertilizer use reminders for ensuring access to HIV medical assistance). The general conclusion is that with the use of small precautionary measures results in significant improvement in outcomes.

Controlling for non-cognitive skills in analyzing farm production outcomes remains an unexplored topic in the discipline. Farmers may be vulnerable to stress resulting from unpredictable weather or output prices. They are subject to time pressures, changes in government policies, and farm hazards. Many farmers are geographically isolated. Unanticipated events might generate psychological pressure [Willock et al., 1999]. These considerations provide the motivation for including emotional and personality variables in agricultural production functions. In this chapter, we assess the role of non-cognitive skills in affecting productive efficiency (the ability to produce more from the same inputs) and/or affecting allocative efficiency (use a more or less efficient combination of inputs). We use cross-sectional data for 501 households in rural villages in the Amhara and Oromya regions of Ethiopia during the crop year 2012. We integrate information on non-cognitive skill measures into standard production function estimates to account the `unobservable' factors that may affect household decision-making (such as mindset, entrepreneurship and aspiration).

The remainder of the chapter is organized as follows: section two presents empirical framework adopted on agricultural productivity; while section three and four present the estimation results for productivity using non-cognitive skills measures. Section 5 concludes.

1.2. Agricultural Productivity: Empirical Framework and Evidence

In this chapter and the following one, we address two issues: a) the role of non-cognitive skills in affecting productive efficiency (the ability to produce more from the same inputs); b) how non-cognitive skills affect allocative efficiency (use of a more or less efficient combination of inputs). In this specific chapter, we address the first point and the associated literature.

The standard method for measuring and modeling differences in technical efficiency in agricultural productivity is through the estimation of production functions. Production functions represent the technological relationship between output and factor inputs. The literature considers different explanations for disparities in agricultural productivity. We briefly survey these in what follows.

- Many development interventions have aimed to reduce the gender gaps in health, education and nutritional status. There is considerable evidence of gender differences in agricultural productivity. A number of possible factors may lead to agricultural productivity differences between men and women such as lack of access to productive resources and low levels of human capital. The literature on the specific productive necessities of poor female farmers is relatively limited and it is typically confined to a single factor – land - [Quisumbing and Pandolfelli, 2010]. Peterman et al. (2011), for example, show persistently lower productivity on female-owned plots and among female-headed households in Nigeria and Uganda.
- Technology adoption (allocation and adoption of inputs) is identified as the key to improving agricultural productivity in Africa [Doss, 2001].
- Extension services may help the spread of agricultural inputs usage. Owens et al. (2003) show that in Zimbabwe, after controlling for innate productivity characteristics and farmer ability and village fixed-effects, access to agricultural extension services raises the value of crop production by 15%.
- Credit is often a prerequisite for the adoption of improved seeds and fertilizers: a farmer's ability to obtain credit may be correlated with land tenure and agricultural productivity itself. Thus, large-scale farmers who produce for the market may have better access to credit than small-scale farmers [Doss, *ibid*.]. The impact of fertilizers and seeds on agricultural productivity depends on availability and proper application on the plot. Again, extension services may improve knowledge and implement recommendations to smallholders. Asia's green revolution was successfully achieved through wholesale supply strategies aimed at extending the use of fertilizers. Supply problems have been widely cited to explain why farmers do not purchase and use fertilizer. For example, because the African continent's agro-ecological zones are more diverse than Asia's these strategies may not produce the same yield results in Sub-Saharan Africa [Voortman et al., 2000]

Against this background, we analyze how emotional and attitudinal factors affect agricultural outcomes. We start with a standard neoclassical production function defined by

$$Y_i = f(V_i, X_i)$$

where Y_i is the quantity produced on plot i; V_i is a vector of inputs used on plot i (land, labor, capital) and X_i is a vector of individual attributes. Typically, empirical studies estimating farming productivity use the translog or Cobb-Douglas specifications, the latter being a special case of the former. Both functional forms are linear in parameters and, conditioning on input choices, can be estimated using OLS. Zellner et al. (1966) argue that input decisions are made to maximize expected, not actual profits, prior to revelation of the production function disturbance. This assumption allows consistent estimation of the conditional representation by OLS. The assumption is reasonable if the production function disturbance represents the impact of unanticipated post-planting weather shocks. If the disturbance also comprises omitted factors which potentially also influence input choices, OLS estimates will be inconsistent. The omission of the emotional-attitudinal variables (as well as other omitted variables) may therefore result in inconsistency in standard neoclassical production function estimates.

If we possessed information on the inputs used for each crop, we would be able to compute distinct production function for each crop using crop yield as the dependent variable. More usually, the data do not permit allocation of inputs across crops and intercropping may imply that some inputs, for example, fertilizers, may not be crop-specific. This is the case with our data and we follow Owens et al. (2003), Liu (2006) and Peterman et al. (2011) in using an output index. The multi-crop output Y_i is a measure of value of crop yield per area unit calculated as quantity produced for each crop per hectare (y_{ik}) multiplied by caloric intake of that specific crop (c_k) $Y_i = \Sigma(y_{ik} * c_k)$.

We can assume a vector of personality traits B_i that affect outcomes Y_i and input adoption V_i, such that the model become:

$$Y_i = f(V_i, X_i, B_i)$$

Vector B_i may explain farmers' reactions to negative events: farmers with strong endowment of both cognitive (making use of extension services, years of education etc.) and non-cognitive abilities (conscientiousness and willingness to work for long-term goals) may overcome short-term or temporary negative shocks through long-term commitment to pursuing farming activities. Farmers without enduring personality traits or strong cognitive abilities may be more likely to abandon agriculture activities [Savastano, 2013]. Smallholders' choices in the adoption of new input technologies to enhance agricultural productivity may also depend on their aspiration levels. If they form mental models which ignore some options for investment. Behavioral variables may affect both yield directly and also indirectly through input use. Policies directed towards increasing the supply of fertilizers and seeds may not lead to the expected results if non-rational perceptions of investments are not taken into account.

1.3. Empirical Strategy

We estimate a production function including proxies for personality traits to check if they concur to affect the farming production process. Production function relates the physical output of a production process to the physical inputs or factors of production. The simplest technical specification is the Cobb-Douglas function:

$$\ln Y_i = \delta_0 + \sum_{j=1}^{k} \beta_j \ln V_{ij} + \alpha_2' X_i + \alpha_3' B_i + \delta' W_i + \epsilon_i \quad (1)$$

$$\forall\, i = 1, \ldots, N$$

where the subscript i identifies the plot field. Y_i is the total output of plot i (crop yield per area unit, weighted by crop caloric intake[15]); V_{ij} is the jth agricultural input (including family labor, quantity of fertilizer seeds, crop area, quality of the soil) applied on plot i; X_i is a vector of the characteristics of the household operating plot i (female-headed household, household head age, average educational attainment in the household, household size, access to credit and extension services, number of plows and bikes owned) , B_i is a vector of behavioral and personality variables relating to the household members working on farming plot i[16] and ε_i is an error term. We control for geographical differences with m dummy variables W for administrative *woreda* levels. We restrict the sample to those plots on which a single crop variety is cultivated.

We estimate also another possible specification for agricultural productivity using a translog production function.

$$\ln Y_i = \delta_0 + \sum_{j=1}^{k} \beta_j \ln V_{ij} + \frac{1}{2} \sum_{h=1}^{k} \sum_{j=1}^{k} \beta_{hj} \ln V_{ih} \ln V_{ij} + \alpha_2' X_i + \alpha_3' B_i + \delta' \ W_i + \epsilon_i \qquad (2)$$

$$\forall\, i = 1, \ldots, N;$$

The translog production function specializes to the Cobb-Douglas form if $\beta_{il} = 0$. We test these restrictions using a Wald test. We control for geographical differences with a set of m dummy variables W where $W_{ij} = 1$ if plot j is in woreda i. We distinguish $k = 5$ input variables usually utilized in farming production function

[15] We try to restrict the agricultural output to different crop-categories (such as cereal, and other crops) and most cultivated crop (such as teff, barley, and sorghum). We omit to present the results since the small N of the regressions do not produce reliable estimates

[16] We use the average BFI (agreeableness, conscientiousness, neuroticism, extraversion and openness) and ER (suppression and reappraisal) scores of household members working on the plot. We tried different specifications with no great difference on the estimated results: disaggregating averages of BFI and ER scores by the gender of household members, and using the scores of the household head

analysis: plot area (ha), the quantity of fertilizers applied per hectare (kg/ha), quantity of seeds used per hectare (kg/ha), family labor person per day per hectare, and having a low-quality plot. The pure neoclassical specification usually includes only input variables, however household characteristics may affect the agricultural output and are often included in the estimation. The household characteristics vector *X* has eight components: a dummy variable for a female household head, the household head age, the average schooling level in the household, household size per adult equivalent, a dummy which takes the value one if the household during last year has received a loan outstanding 100 BIRR or more, a binary variable to account extension services, and number of plows and bikes owned to account for agricultural asset and wealth in the household.

As anticipated in the previous section, personality traits might affect performance on a task, controlling for cognition, other skills, and effort applied. In addition, the effort allocated to the task, in this case, agriculture production, depends on cognition, personality traits, incentives and also preferences. Personality traits are largely inherited, but it is also possible that the may be modified by the social environment over time [Roberts, 2009].

We are aware of the limitations that such a small sample could generate -the most important- the limited external validity of our results. However, even though the sample is not representative for Ethiopa, we believe that this empirical exercise still may shed light on the impact of non-cognitive skills on agricultural output. We also mention beforehand the possibility of measurement errors affecting at a certain degree the reliability of our behavioral measures. The extensive descriptive section presented above tries to isolate the noise and correlation between the different sets of variables.

We estimate both the Cobb-Douglas and translog functions as specified above using Ordinary Least Square (OLS) and also **four cases**:

a) A base specification which sets both the α and β coefficients to zero. This provides the base in which we can measure fit using an adjusted R^2 statistic [Table 1 in the appendix I];
b) The pure neoclassical specification that sets the α coefficients associated with the household and behavioral variables to zero. Again, we estimate both the translog and Cobb-Douglas versions [columns 1-2 Table 1 in the text];
c) The standard classification without behavioral variables [columns 3-4 Table 1 in the text];
d) The general case defined by equation (2) and also the Cobb-Douglas simplification (1) [columns 5-6 Table 1 in the text].

Full estimates with heteroscedasticity-robust standard errors are reported in Appendix I Table 1 and 2. While Table 1 in the text present in a more concise way the extensive results reported in the appendix I.

The gradual addition of different sets of variables allow us to statistically control whether adding certain variables increase the explanatory power of each specification. The main aim is to assess whether inserting behavioral variables in the estimation positively affect the explanatory power of the production function. We try to isolate at the best the `noise' coming from the other variables (geographical locations, inputs and household characteristics).

The OLS estimation is a basic estimation tool. However, under reasonable assumptions about the disturbance term the inputs can be shown to be independent of the disturbance term of the production function. Therefore, OLS estimation method gives consistent and unbiased estimates. However, observed inputs may be correlated with unobserved shock and therefore hinder the reliability of the OLS estimates. The most common solutions offered by the literature are the instrumental variable approach and using longitudinal panel data. Regarding the first solution the researcher should find a variable that is correlated with the variable input and uncorrelated with the shock. A possibility is to use input prices as instrument. However, as in our case, exogenous input prices are not observed. Furthermore, even when these prices are observed they could not vary by farm or the variation itself may be correlated with the error. Aware of the possible shortcomings of the OLS estimation we are constrained to rely on it because of the cross-sectional nature of the survey design and the lack of a proper exogenous and relevant instrument to use.

Results for the full model are shown in Table 1 and summarized the fit of the six production functions in terms of standard error, R^2 , and AIC[17]. For equations (1)-(2) we also give the R^2 statistic relative to the equation with only administrative dummy variables, i.e. netting out explanation due to woreda dummies [Table 1 in the appendix I]. Adding a set of variables (household characteristics and non-cognitive skills measures) to regressions progressively decreases AIC statistics, while the R^2 statistic relative to the equation in table 1 increases. In particular, adding the set of non-cognitive skills measures to Cobb-Douglas and translog models increases the R^2 statistic relative to the base woreda equation by 12 and 8 percentage points, respectively.

To assume a linear relationship between the outcome and traits could be problematic since extreme levels of traits are associated with Obsessive Compulsive Disorder which hinders task performance [Samuel and Widiger, 2008]. In order to choose the correct specification for non-cognitive skills variables, we tried different specification (linear, quadratic and cubic).

Two robustness checks are performed: we re-estimate OLS excluding observations with farm size greater than 5 hectares [results not presented], and we use the output index weighted by unit prices [Table 2b Appendix I] in place of calorific values. The two different specifications return similar results so we limit the comments to the results obtained using as independent variable the crop yield weighted by the caloric intake.

We tested whether a reduced model for production function is preferred to the full model specification: we show F-test results in table 1 for Cobb-Douglas and translog (with quantity variables in the first row and using dummy variables for inputs in row 2). We then performed a restricted Hausman test between Cobb-Douglas specification without and with behavioral variables. The null hypothesis is that the coefficients on the factor input variables reported in column (3) and (5) are not statistically different amongst the two models. These results allow us to conclude that omission of the behavioral measures from the estimation leads to inconsistent estimates for the production function

Table 2 in the appendix I summarize fit of regression adding a set of variables. The first two columns report results for Cobb-Douglas and translog production function using only inputs variables. In columns (3) and (4) we add household characteristics, and finally, in columns (5) and (6), we present full model specification results with non-cognitive skills measures.

The analysis focuses on the estimation of different specifications of the production functions. However, a well-established stream of literature uses production function estimation as the first step in deriving conclusions on the input efficiency. Using an estimated production frontier it is possible to measure the relative efficiency of certain groups or set of practices from the relationship between observed production and some ideal or potential production [Greene, 1993]. We started this work with the intention of undertaking stochastic frontier estimation estimation using non-cognitive skills as a source of technical inefficiency of the agricultural

[17] The Akaika Information Criterion (AIC) is a widely used criterion for model selection. The AIC rule suggests selection of the specification which minimizes the AIC. The AIC modifies the likelihood of the model (L) to penalize the number of parameters estimated (k): $AIC = 2k - 2\ln(L)$. Akaike (1974) showed that the AIC estimates the difference in the losses from two alternative specifications. In the linear regression model, $AIC = n[1 + \ln(2\pi)] + n\ln(\hat{\delta}^2) + 2k,$ the minimization of AIC requires minimization both of RSS (and hence $\hat{\delta}^2$) and the number of parameters k. This forces a balance between parsimony (small k) and high fit (low $\hat{\delta}^2$).

output. However, we chose to not continue to pursue this objective since the results were inconclusive. The analysis is summarized in Appendix II.

1.4.Detailed discussion of the results

In the previous paragraph we presented the empirical strategy and how we chose to split the estimation results amongst the tables in the text. In this section we focus on commenting the results we obtained.

First of all, we must keep in mind the purpose of the empirical estimation. We want to isolate the effect of inserting the behavioral variables of the household members working on the plot into the estimation of two different specifications of production function (Cobb-Douglas and translog) of the agricultural output. The regressions are performed restricted on the plot where only one variety of crop is cultivated, each crop yield is weighted by the caloric intake of the crop.

Input coefficients translog specification: Extended results are presented in table 2 in the appendix I. The estimated translog coefficients for the quantity of seeds and fertilizers used on the plot define an inverse U-shaped function while the reverse is true for family labor per person per day[18]. The relationship between crop area cultivated and productivity is monotone positive. Figure 1 shows graphically the predicted margins for translog input coefficients. It is worth commenting on their shape. The first panel on the left, suggests concave predicted impacts of higher levels of quantity of seeds used on the plot on increasing farming output. Increases in quantity of seeds used are most significant at lower parts of the distribution. At the same time, predicted impacts decrease when moving up the distribution after reaching the optimal point of quantity of seeds applied. The second panel on the right shows predicted margins for fertilizer applied per hectare. Again, we notice concave predicted impacts but after reaching the turning point of the function margins rapidly decreases, i.e. the application of too much quantity of fertilizer on the plot is associated with a sharp decrease in output. A possible explanation could be that farmers try to compensate low quality of the cultivated soil over-applying fertilizer to protect the productivity of the crop. Moreover, researchers have established the negative impacts of using fertilizers on farmer agricultural land which causes the degradation of the surface land, and long-term depletion of organic matter and soil compaction [Sullivan, 2004]. This conjecture is reinforced by the descriptive statistics. On average farmers apply a larger quantity of fertilizer on low-quality plots[19]. Last, we comment family labor per day. Output per family worker initially declines and then almost increased in a nearly linear manner after the turning point. As documented by Lewis (1954), Kuznets (1966), and Timmer (1988), the start of economic growth in poor labor-abundant countries requires a prior sustained rise in per capita productivity in the agricultural sector since otherwise, the agricultural sector is unable to respond to the augmented urban demand for agricultural products. Increased agricultural productivity creates a surplus which is used to develop the non-agricultural sector. A failure of agricultural productivity to rise would result in food price inflation that would inhibit growth in the non-agricultural sector. The shape of family labor per day coefficient seems to reflect this path: at the beginning agricultural output is not rising meaning that agricultural sector contains potential surpluses of labor time (confirmed by descriptive statistics), then after releasing some labor forces to other economic sector output per worker starts to rise after the turning point.

Household Characteristics' coefficients: Including household characteristics and then non-cognitive skills measures either in the Cobb-Douglas and translog specifications we notice that estimated marginal effects alter coefficients with the claim that production functions that omit these variables give biased estimates for marginal effects for the inputs. Marginal effects increase for both specifications, except for quantity of seeds used which decrease for Cobb-Douglas specification when introducing non-cognitive skills measures.

[18] We checked whether there are data both sides of turning point to assess if the sign of the derivative is a feature of the data or an extrapolation of the functional form outside the range of sample variation.

[19] On average on low quality plot is applied 71 Kg more compared to other soil quality. However, this difference is not statistically significant

Turning to the vector of household characteristics X in the fully specified model in the appendix I, larger families are more productive than smaller ones. Non-agricultural assets (number of bikes owned) are associated with a decrease in agricultural productivity. A possible explanation is that the primary activity of wealthy households, where wealth is assessed in terms of asset ownership, is non-agricultural. For example, the data show a positive correlation between both bicycle and radio ownership and gross aggregated income, and a negative correlation with agricultural income [results not shown].

Behavioral coefficients: We finally comment the vector of the behavioral variables. Table 2 in the appendix I reports the estimated coefficients for each personality construct. We inserted a weighted average of the scores of the family members that reported to have worked on the plot. The significant coefficients are stables across the two different specifications and have similar magnitude. Conscientiousness, neuroticism and suppression traits positively affect the agricultural outcomes, while openness is negatively associated to the production. A possible explanation could be that organizational skills, reliability along with a certain degree of psychological pression caused by high level of neuroticism may help increase the yield on farm. Ethiopian farmers may be engaged in farming activities under harsh conditions and external pressure depending on favorable rain to cultivate. High level of stress may help or may be caused by this environment displaying a positive coefficient in the production function. The positive sign of emotional suppression may be a consequent result of the positive relationship of the neuroticism trait. Suppression occur after the individual is exposed to strong emotional external stimuli suppressing the subsequent distress. The negative sign of openness to experience show that success on farm and intellectual enthusiasm for the novelties is not verified. Given that the selected sample displayed already high level of compliance regarding the use of agricultural technology input on farm the trait may not necessary capture this attribute. Excessive openness may even cause farmers to switch occupation outside the farm. Therefore, this confirm at a certain degree the speculation mentioned beforehand that farmers may be associated to the most conservative segment of the population.

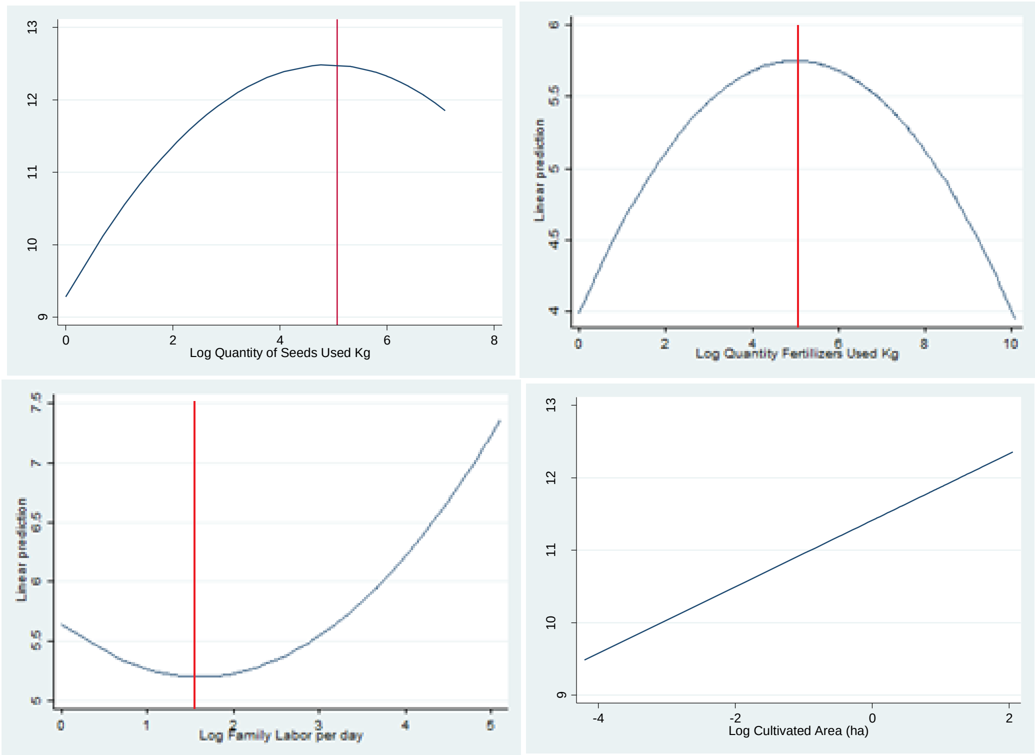
Table 1 Estimated Marginal effects for Inputs; AIC and R^2; F-test and Wald-test

	(1) Input only: Cobb-Douglas	(2) Input only: Translog	(3) Input + HH Characteristics: Cobb-Douglas	(4) Input + HH Characteristics: Translog	(5) Input + HH Characteristics+ Non-cogn: Cobb-Douglas	(6) Input + HH Characteristics+ Non-cogn: Translog
Predicted Margins						
Log Seed Used (kg)	**0.495*** **	**0.151*** **	**0.492*** **	**0.158*** **	**0.456*** **	**0.192*** **
	[15.00]	[3.58]	[14.70]	[3.86]	[13.61]	[4.57]
Log Fertilizers Used (kg)	-0.0227	0.0621	-0.0316	0.0540	-0.0298	0.0246
	[-0.553]	[1.52]	[-0.765]	[1.34]	[-0.694]	[0.59]
Log Family Labor (person per day)	0.108	**0.318*** **	**0.125***	**0.323*** **	**0.154*** **	**0.329*** **
	[1.560]	[4.47]	[1.816]	[4.50]	[2.257]	[4.31]
Dummy for low quality soil	0.0899	0.0308	0.129	0.077	0.0526	0.0442
	[0.786]	[0.30]	[1.137]	[0.75]	[0.479]	[0.42]
Log Crop Area Tot (ha)	**0.340*** **	**0.350*** **	**0.326*** **	**0.352*** **	**0.450*** **	**0.443*** **
	[3.546]	[3.79]	[3.375]	[3.82]	[4.742]	[4.90]
R-squared	0.560	0.654	0.579	0.667	0.641	0.700
AIC†	**3150**	**2971**	**3128**	**2953**	**2668**	**2558**
Residula Sums of Squared	1907	1500	1825	1441	1340	1120
R^2 Corrected††	**0.520**	**0.623**	**0.541**	**0.638**	**0.663**	**0.718**
F-Test*						
Test Statistics	2.8431068	2.17995				
Confidence Interval	1.2697697	1.2701636				
P-value	0.000	0.000				
Wald-Test*						
F		17.37		16.45		9.34
Prob>F		0.000		0.000		0.000
Hausman Test**						
Chi(5)			127.3889			
P-value			0.000			

*** p<0.01, ** p<0.05, * p<0.1
Robust Std Errors

† The **AIC** rule suggests selection of the specification which minimizes the AIC. the minimization of AIC requires minimization both of RSS (and hence $\hat{\delta}^2$) and the number of parameters k. This forces a balance between parsimony (small k) and high fit (low $\hat{\delta}^2$).
†† **R^2 Corrected** using the R2 statistic relative to the equation with only administrative dummy variables, i.e. netting out explanation due to woreda dummies.
***F-test** between reduced Cobb-Douglas/Translog models against extended models with non-cognitive skills variables. We reject the null hypothesis of reduced models being equal to the extended one.
****Wald-test** is used in order to test restrictions $\beta_{il} = 0$ for Translog models.
*****Hausman Test** performed between Cobb Douglas regressions without/with noncognitive skills, both regressions include household characteristics. We restricted a number of coefficients tested (log seed used, log fertilizer, log family labor, dummy for low quality, log crop area). Null hypothesis H_0:E [3]=E[5]. We reject the null hypothesis estimated inputs coefficients are different between the two models

Figure 1 Predicted Margins for Translog Model (full specification with household characteristics and non-cognitive skills)



Log Quantity of Seeds Used: turning point: 5.069 (336 obs before, 870 after)
Log Fertilizer Used: turning point: 1.573 (555 obs before, 651 after)
Log Family Labor per day: turning point 4.733 (98 obs before, 1108 after)

1.5. Conclusions

The human capital literature has expanded over the past two decades to take into account non-cognitive abilities. In this chapter, we estimated production functions for a sample of Ethiopian farmers in 2012, integrating standard household characteristics with non-cognitive skills as measured by BFI and ER tests. Without the presumption to be exhaustive, in this chapter we responded the first of two connected issues: a) the role non-cognitive skills in affecting productive efficiency (the ability to produce more from the same inputs); and b) how non-cognitive skills affect allocative efficiency (use a more or less efficient combination of inputs). We are aware of the possible limitations of the results, especially in terms of representativeness of the national population of Ethiopia and the possible measurement errors hindering the reliability of our behavioral constructs. Also, another threat to the reliability of our results is represented by the possible endogeneity of the stock of the non-cognitive skills across villages. Since a large component of those trait is inherited and the social environment may as well shape those traits, household members living in the same village will likely have similar endowment of skills.

The estimation of farm-level productivity is a well-known topic in the economic literature. However, there are various difficulties during the estimation. Zellner et al. (1966) represents a first attempt to correct such problems in the estimation. The fact is that farmers observe idiosyncratic shocks and adjust their input choices accordingly. Moreover, the inclusion of non-cognitive skills might reduce bias to `unobservables' in empirical estimation making observable the unobservable variables that may affect household decision-making.

The yield analysis is performed on plot-level data using translog and Cobb-Douglas production function specifications. The results indicate that there is a contribution of non-cognitive skills in explaining agricultural productivity. When introducing the set of non-cognitive skills variables in the estimation of the Cobb-Douglas model we found that inputs coefficients change (they increase for all inputs except for the quantity of seed used). This is confirmed by a Hausman test restricted on the coefficients of the input variables. The coefficients of household characteristics lose statistical significance (average schooling in the household, number of plows and being under extension services) implying that these characteristics to some extent proxy more fundamental behavioral variables. Similar results are found also for the translog specification. Moving to the behavioral measures, – higher scores for conscientiousness, neuroticism, and suppression are all associated with a positive and statistically significant effect on agricultural productivity Organizational skills, reliability, a strong capacity to "suppress" external emotional stimulus, and a high level of anxiety all appear to be yield-enhancing psychological characteristics. The results for the neuroticism measure merit comment. It is possible that a degree of `psychological pressure' is required in order to successfully perform agricultural tasks but that too much anxiety results in insecurity which depresses yields. High levels of neuroticism may also reflect the distress caused by the lack of other economic opportunities outside agriculture `trapping' households on farming activities. This is also in line with the economic concept of `procedural utility' [Frey et al., 2004], which in turn relies on self-determination theory (SDT) [Deci and Ryan 1985, 2004]. People are said to obtain procedural utility when their well-being is affected not only by the final outcomes they achieve but also by the process of reaching those outcomes [Markussen et al., 2017]. Omitting behavioral variables in the estimation of the production function could lead to possible misleading results: overestimating the effect of certain variables respects to other, for example. This is confirmed by the R^2 and AIC statistics reported, and also by F, Wald and Hausman tests. We discuss extended policy implications in the final conclusions in the next chapter after takin in account the household input adoption choices.

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APPENDIX I

Table 1 OLS regression base estimates excluding economic and behavioral variables

VARIABLES	Output (unit price weights) (1) Woreda and Intercept	Output (caloric intake weights) (1) Woreda and Intercept
Woreda (Lasta)	-0.307	-0.145
	[-1.420]	[-0.690]
Woreda (Sirba)	**0.426****	**0.357***
	[2.150]	[1.886]
Woreda (Adele Keke)	**-0.331***	**0.422****
	[-1.678]	[2.321]
Woreda (Koro Degaga)	**1.267*****	**1.169*****
	[6.616]	[6.309]
Woreda (Turfe)	**-0.785*****	-0.0883
	[-2.835]	[-0.343]
Woreda (Basona Werana)	**-2.823*****	**-2.374*****
	[-11.18]	[-9.441]
Constant	**5.963*****	**11.84*****
	[33.87]	[69.67]
Observations	1,297	1,191
R-squared	0.325	0.290
AIC	5379	4830
Residual Sums of Squared	4751	3978
R^2 Corrected		

*** p<0.01, ** p<0.05, * p<0.1
Robust Std Errors

Table 2a Output Index weighted by crop caloric intake

VARIABLES	(1) Input only: Cobb-Douglas	(2) Input only: Translog	(3) Input + HH Characteristics: Cobb-Douglas	(4) Input + HH Characteristics: Translog	(5) Input + HH Characteristics+ Non-cogn: Cobb-Douglas	(6) Input + HH Characteristics+ Non-cogn: Translog
Woreda (Lasta)	-0.113	0.105	-0.0347	0.157	-0.227	0.0204
	[-0.599]	[0.507]	[-0.173]	[0.748]	[-1.158]	[0.102]
Woreda (Sirba)	0.149	**0.267***	**0.303***	**0.395****	**0.629*****	**0.602*****
	[0.897]	[1.673]	[1.661]	[2.327]	[3.283]	[3.342]
Woreda (Adele Keke)	0.236	**0.506*****	0.0933	**0.402****	0.185	**0.462***
	[1.467]	[3.126]	[0.477]	[2.090]	[0.796]	[1.959]
Woreda (Koro Degaga)	**0.852*****	**0.800*****	**0.854*****	**0.814*****	**1.015*****	**0.911*****
	[4.700]	[4.332]	[4.256]	[4.156]	[4.797]	[4.306]
Woreda (Turfe)	**0.492****	**0.584****	**0.583****	**0.674*****	**0.777*****	**0.828*****
	[2.039]	[2.582]	[2.296]	[2.863]	[2.906]	[3.354]
Woreda (Basona Werana)	**-1.255*****	**-0.920*****	**-0.919*****	**-0.634*****	**-0.704*****	**-0.500****
	[-5.376]	[-4.123]	[-3.708]	[-2.741]	[-2.862]	[-2.156]
Inputs						
Log Seed Used (kg)	**0.495*****	**1.633*****	**0.492*****	**1.585*****	**0.456*****	**1.318*****
	[15.00]	[13.90]	[14.70]	[13.20]	[13.61]	[10.21]
Log Fertilizers Used (kg)	-0.0227	**0.851*****	-0.0316	**0.859*****	-0.0298	**0.675*****
	[-0.553]	[4.251]	[-0.765]	[4.299]	[-0.694]	[3.251]
Log Family Labor (person per day)	0.108	**-0.746****	**0.125***	**-0.664****	**0.154****	**-0.755****
	[1.560]	[-2.264]	[1.816]	[-2.003]	[2.257]	[-2.160]
Dummy for low quality soil	0.0899	0.589	0.129	0.703	0.0526	**0.854***
	[0.786]	[1.281]	[1.137]	[1.497]	[0.479]	[1.819]
Log Crop Area Tot (ha)	**0.340*****	-0.0239	**0.326*****	-0.00374	**0.450*****	0.0904
	[3.546]	[-0.0822]	[3.375]	[-0.0124]	[4.742]	[0.285]
Translog Inputs Terms						
Log Seeds Used Squared		**-0.179*****		**-0.174*****		**-0.130*****
		[-10.14]		[-10.02]		[-7.177]
Log Fert Used Squared		**-0.0735*****		**-0.0745*****		**-0.0713*****
		[-3.456]		[-3.622]		[-3.195]
Log Family Labor Squared		**0.257*****		**0.248*****		**0.240*****
		[3.586]		[3.484]		[3.204]
Log Crop Area Tot Squared		0.0857		0.0674		0.0409
		[0.674]		[0.536]		[0.318]
Log Seeds Used* Log Fert Used		0.00521		0.00789		0.00157
		[0.304]		[0.463]		[0.0896]
Log Seeds Used* Log Family Labor		-0.00117		-0.00119		-0.00182
		[-0.890]		[-0.925]		[-1.405]
Log Seeds Used*Low Quality		**-0.112****		**-0.116****		**-0.0988***
		[-2.243]		[-2.321]		[-1.915]

	(1)	(2)	(3)	(4)	(5)	(6)
Log Seeds Used*Log Crop Area Tot		0.0155		0.0172		0.0155
		[0.762]		[0.873]		[0.803]
Log Fert Used*Log Family Labor		-0.0458		-0.0489		0.00633
		[-0.826]		[-0.928]		[0.105]
Log Fert Used*Low Quality		-0.0949		-0.102		-0.0901
		[-1.390]		[-1.529]		[-1.325]
Log Fert Used*Log Crop Area Tot		**0.104****		**0.0924***		0.0874
		[2.002]		[1.718]		[1.588]
Log Fam Labor*Low Quality		0.152		0.135		0.00619
		[1.314]		[1.191]		[0.0542]
Log Fam Labor*Log Crop Area Tot		-0.0494		-0.0481		-0.0476
		[-1.229]		[-1.190]		[-1.157]
Low Quality*Log Crop Area Tot		-0.112		-0.0475		0.0473
		[-0.704]		[-0.300]		[0.294]
<u>Household Characteristics</u>						
Dummy for Female Household Head			-0.143	-0.0656	0.0150	0.0107
			[-1.024]	[-0.515]	[0.102]	[0.0798]
Household Head Age (years)			0.00468	0.000353	0.00475	0.000734
			[0.421]	[0.0358]	[0.443]	[0.0729]
Household Average Schooling			**-0.0446***	-0.0313	-0.0392	-0.0314
			[-1.804]	[-1.417]	[-1.558]	[-1.374]
Household Size per adult equivalent			**0.106*****	**0.0688***	**0.118*****	**0.0888****
			[2.601]	[1.683]	[3.011]	[2.170]
Dummy for Obtained Credit			0.0693	0.0976	-0.0154	0.0354
			[0.631]	[0.946]	[-0.136]	[0.324]
Number of Plough			**-0.116***	**-0.107****	-0.0814	-0.0784
			[-1.962]	[-1.983]	[-1.117]	[-1.106]
Number of Bikes			**-0.499*****	**-0.600*****	**-0.689*****	**-0.727*****
			[-2.717]	[-3.236]	[-3.723]	[-3.939]
Dummy for Extension Services			**0.911*****	**0.767*****	0.378	0.395
			[3.380]	[3.241]	[1.169]	[1.343]
<u>Big Five Inventory T-Scores (Family Members working on plot)</u>						
Extraversion					-0.00618	0.00394
					[-0.537]	[0.370]
Agreeableness					0.00202	0.00339
					[0.252]	[0.452]
Conscientiousness					**0.0205***	0.0117
					[1.842]	[1.155]
Neuroticism					**0.0378*****	**0.0266*****
					[3.484]	[2.665]
Openness					**-0.0370*****	**-0.0229*****
					[-4.050]	[-2.722]
<u>Emotion Regulation Score (Family Members working on plot)</u>						
Suppression					**0.304*****	**0.285*****
					[7.640]	[7.380]
Reappraisal					0.0850	0.00949
					[1.337]	[0.145]
Constant	**9.251*****	**7.058*****	**8.046*****	**6.045*****	**5.911*****	**4.567*****
	[28.27]	[9.223]	[14.94]	[7.032]	[5.023]	[3.480]
Observations	860	860	860	860	771	771
R-squared	0.560	0.654	0.579	0.667	0.641	0.700
AIC	**3150**	**2971**	**3128**	**2953**	**2668**	**2558**
Residula Sums of Squared	1907	1500	1825	1441	1340	1120
R^2 Corrected	**0.520**	**0.623**	**0.541**	**0.638**	**0.663**	**0.718**

*** p<0.01, ** p<0.05, * p<0.1
Robust Std Errors

Table 2b OLS Regressions for Log Output Index (unit price): Final Models [Robustness Check]

VARIABLES	(1) Input only: Cobb-Douglas	(2) Input only: Translog	(3) Input + HH Characteristics: Cobb-Douglas	(4) Input + HH Characteristics: Translog	(5) Input + HH Characteristics+ Non-cogn: Cobb-Douglas	(6) Input + HH Characteristics+ Non-cogn: Translog
Woreda (Lasta)	-0.307	-0.118	-0.261	-0.102	**-0.374***	-0.192
	[-1.585]	[-0.555]	[-1.283]	[-0.477]	[-1.881]	[-0.943]
Woreda (Sirba)	0.200	**0.285***	**0.344***	**0.406****	**0.719*****	**0.668*****
	[1.129]	[1.667]	[1.801]	[2.261]	[3.586]	[3.499]
Woreda (Adele Keke)	**-0.393****	-0.162	**-0.543*****	-0.281	-0.319	-0.0561
	[-2.299]	[-0.950]	[-2.632]	[-1.384]	[-1.315]	[-0.232]
Woreda (Koro Degaga)	**0.953*****	**0.878*****	**0.899*****	**0.842*****	**1.170*****	**1.044*****

	[5.415]	[5.023]	[4.559]	[4.469]	[5.778]	[5.342]
Woreda (Turfe)	-0.201	-0.102	-0.0966	0.00412	0.223	0.251
	[-0.764]	[-0.419]	[-0.359]	[0.0167]	[0.790]	[0.949]
Woreda (Basona Werana)	**-1.765*** **	**-1.464*** **	**-1.471*** **	**-1.217*** **	**-1.159*** **	**-0.984*** **
	[-7.524]	[-6.674]	[-5.958]	[-5.316]	[-4.771]	[-4.345]
Inputs						
Log Seed Used (kg)	**0.488*** **	**1.632*** **	**0.484*** **	**1.598*** **	**0.457*** **	**1.366*** **
	[15.64]	[14.48]	[15.31]	[13.97]	[14.34]	[11.00]
Log Fertilizers Used (kg)	-0.0252	**0.936*** **	-0.0314	**0.929*** **	-0.0297	**0.792*** **
	[-0.621]	[4.349]	[-0.764]	[4.367]	[-0.695]	[3.517]
Log Family Labor (person per day)	**0.166** **	**-0.562* **	**0.184*** **	-0.465	**0.236*** **	**-0.580* **
	[2.453]	[-1.729]	[2.737]	[-1.435]	[3.518]	[-1.929]
Dummy for low quality soil	0.0139	**0.842* **	0.0529	**0.982** **	-0.00880	**1.171** **
	[0.124]	[1.749]	[0.471]	[2.013]	[-0.0795]	[2.415]
Log Crop Area Tot (ha)	**0.356*** **	-0.0944	**0.356*** **	-0.0438	**0.481*** **	0.0222
	[3.885]	[-0.339]	[3.896]	[-0.152]	[5.436]	[0.0733]
Translog Inputs Terms						
Log Seeds Used Squared		**-0.173*** **		**-0.169*** **		**-0.130*** **
		[-10.37]		[-10.30]		[-7.468]
Log Fert Used Squared		**-0.0738*** **		**-0.0728*** **		**-0.0698*** **
		[-3.527]		[-3.613]		[-3.234]
Log Family Labor Squared		**0.243*** **		**0.233*** **		**0.260*** **
		[3.304]		[3.226]		[3.754]
Log Crop Area Tot Squared		0.114		0.101		0.0901
		[0.947]		[0.842]		[0.735]
Log Seeds Used* Log Fert Used		0.00510		0.00726		0.00149
		[0.308]		[0.440]		[0.0913]
Log Seeds Used* Log Family Labor		-0.00108		-0.00114		**-0.00197* **
		[-0.856]		[-0.909]		[-1.649]
Log Seeds Used*Low Quality		**-0.128*** **		**-0.137*** **		**-0.113** **
		[-2.638]		[-2.791]		[-2.298]
Log Seeds Used*Log Crop Area Tot		-0.00440		-0.00420		-0.00735
		[-0.250]		[-0.241]		[-0.433]
Log Fert Used*Log Family Labor		-0.0695		-0.0727		-0.0361
		[-1.343]		[-1.462]		[-0.675]
Log Fert Used*Low Quality		**-0.128* **		**-0.141** **		**-0.117* **
		[-1.885]		[-2.121]		[-1.741]
Log Fert Used*Log Crop Area Tot		**0.130** **		**0.123** **		**0.118** **
		[2.572]		[2.361]		[2.203]
Log Fam Labor*Low Quality		0.112		0.104		-0.0761
		[0.941]		[0.896]		[-0.667]
Log Fam Labor*Log Crop Area Tot		-0.0244		-0.0281		-0.0264
		[-0.629]		[-0.730]		[-0.682]
Low Quality*Log Crop Area Tot		-0.153		-0.0991		0.0433
		[-0.966]		[-0.623]		[0.266]
Household Characteristics						
Dummy for Female Household Head			-0.0972	-0.0157	0.0794	0.0778
			[-0.696]	[-0.125]	[0.535]	[0.576]
Household Head Age (years)			0.00541	0.00395	0.00397	0.00196
			[0.547]	[0.445]	[0.403]	[0.212]
Household Average Schooling			**-0.0582** **	**-0.0462** **	**-0.0490* **	**-0.0413* **
			[-2.313]	[-2.050]	[-1.904]	[-1.774]
Household Size per adult equivalent			**0.0950** **	0.0640	**0.0991** **	**0.0737* **
			[2.329]	[1.581]	[2.467]	[1.780]
Dummy for Obtained Credit			0.0374	0.0689	-0.0395	0.0174
			[0.341]	[0.667]	[-0.346]	[0.158]
Number of Plough			-0.0940	**-0.0935* **	-0.0495	-0.0524
			[-1.575]	[-1.729]	[-0.679]	[-0.748]
Number of Bikes			**-0.436** **	**-0.542*** **	**-0.685*** **	**-0.717*** **
			[-2.213]	[-2.888]	[-3.558]	[-3.867]
Dummy for Extension Services			**0.796*** **	**0.662*** **	0.338	0.348
			[2.962]	[2.704]	[1.023]	[1.118]
Big Five Inventory T-Scores (Family Members working on plot)						
Extraversion					-0.00621	0.00362
					[-0.536]	[0.338]
Agreeableness					-0.00146	-0.000979
					[-0.178]	[-0.128]
Conscientiousness					**0.0291*** **	**0.0221** **
					[2.788]	[2.328]
Neuroticism					**0.0501*** **	**0.0395*** **
					[4.810]	[4.092]
Openness					**-0.0326*** **	**-0.0192** **

					[-3.572]	[-2.291]
<u>Emotion Regulation Score (Family Members working on plot)</u>						
Suppression					**0.308*** **	**0.291*** **
					[7.551]	[7.348]
Reappraisal					0.0112	-0.0471
					[0.160]	[-0.673]
Constant	**3.368*** **	0.709	**2.350*** **	-0.182	-0.663	**-2.733** **
	[10.15]	[0.899]	[4.451]	[-0.212]	[-0.593]	[-2.108]
Observations	936	936	936	936	840	840
R-squared	0.579	0.659	0.593	0.669	0.651	0.707
AIC	**3497**	**3328**	**3481**	**3315**	**2987**	**2868**
Residula Sums of Squared	2240	1814	2165	1759	1614	1356
R^2 Corrected	**0.529**	**0.618**	**0.544**	**0.630**	**0.660**	**0.715**

*** p<0.01, ** p<0.05, * p<0.1
Robust Std Errors

APPENDIX II

Technical Efficiency:

Production efficiency is defined as the ability to produce the maximum quantity of output possible given the inputs used: a production function simply defines the technological relationship between inputs and output, assuming all farms as identically technically efficient. Therefore, the production frontier is set by the average farm, variations from this frontier are assumed to be random, perhaps due to unobserved factors of production (land quality etc.). The stochastic production function methodology allows the distinction between random variations in production (a stochastic error component) and an inefficiency component (an additional one-sided error) affecting the reaching of maximal potential output.

Inefficiencies may arise due to structural problems in the market, environmental production conditions, manager skill quality, and other unobservable factors.

Battese and Coelli (1992, 1995) and Battese (1992) define the reference theoretical framework for the stochastic production frontier analysis, taking as a starting point the works of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1997).

Let's assume the following production frontier for a farm $y_i = f(x_i;\beta)TE_i$, where y_i is the output produced by the i-th producer, x is a vector of inputs used by producer i), and TE is the level of technical efficiency for farm i.

Consider the stochastic frontier $y_i = f(x_i;\beta)TE_i \exp(\mathrm{v}_i)$, where $\exp(\mathrm{v}_i)$ captures the effect of random shocks to each producer.

Taking logs on both sides of equation, we obtain the estimating function $\log(y_i) = \alpha + \log(x_i)\,\beta_i + \mathrm{v}_i - u_i$; where $u_i = -\log(TE_i)$, and v_i is a statistical noise assumed to have independently identical symmetric distribution as $N(0,\sigma_{\mathrm{v}}^2)$. While, u_i is distributed as a one-sided normal distribution $N(0,\sigma_u^2)$, this error component captures the effects of inefficiencies relative to the stochastic frontier. The output from ``frontier'' on stata incudes estimates of the standard deviations of the two error components, σ_{v} and σ_u. In the log likelihood they are parametrized as $\ln\sigma_{\mathrm{v}}^2$and $\ln\sigma_u^2$. The estimate of the total error variance, $\sigma_S^2 = \sigma_{\mathrm{v}}^2 + \sigma_u^2$, and the estimate of the ratio of the standard deviation of the inefficiency component to the standard deviation of the idiosyncratic component is $\lambda = \sigma_u/\sigma_{\mathrm{v}}$.

When TE=1 the farm is on the frontier, namely, is producing the optimal output given the technology of the production function; on the other hand, when TE<1 the farm is not making the most of set of inputs x.

However, the (strict) underlying assumption is that all farmers have access to the same technology and that technology may vary across cultivated plots. Furthermore, the stochastic frontier approach suffers from all the problems of specification of the production function (such as the transmission bias).

The production function we try to identify in a first version of the thesis is the following equation:

$$\log(y) = \alpha + \log(x_i)\,\beta_i + \varepsilon_i\ ,$$

$$\text{where } \varepsilon_i = \mathrm{v}_i - u_i$$

where y_i is an agricultural output index; x_i is a set of covariates for each household including agricultural inputs affecting agricultural production and technical efficiency. Amongst factors which affect efficiency the literature identified different sources such as education, wealth level of the household, distance in minutes from the plot, household size, and we add the non-cognitive skills variables. However, there is no standard procedure for separating the two contributions to the deviations of each unit from the supposed true efficiency frontier. In addition, during the estimation we must ignore errors in the output measure, and arbitrarily choose the joint distribution of v_i and u_i and the functional form of the production function. Because of all these theoretical difficulties we do not present the results we obtained for the farmers' technical efficiency use of inputs. One of the main problems was to properly justify why certain variables affect input efficiency rather than the final output. The identification was not so sharp to allow us to assign each variable in the production function or in the inefficiency component. Some variables are likely to have affected both the output and technical efficiency components.

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2.Allocative Efficiency of Agricultural Inputs and Non-cognitive Skills

2.1. Introduction and literature riview

In this section, we address the role played by behavioral variables in affecting the decision to whether and to what extent to adopt agricultural inputs such as seeds and inorganic fertilizers. Research-led technological change in agriculture may generate sufficient productivity growth to give high rates of return in Africa and Asia and could have a substantial impact on poverty [Thirtle et al. 2003]. Moreover, it is generally accepted that SSA farmers often have low yields which could be increased, all else equal, if they bought more `external inputs' (such as chemical fertilizer, pesticides, and seeds) [Adjognon et al., 2016].

African governments and donors have attempted to increase agricultural production by developing policies inspired by the Asian Green Revolution but these policies have generated a little effect in terms of increased use of chemical fertilizers or high yielding varieties [Nin-Pratt and McBride, 2014]. In part, this failure may be due to the different conditions in Africa compared to Asia. Because the African continent's agro-ecological zones are more diverse than those in Asia, these strategies may not produce the same yield results in Sub-Saharan Africa [Voortman et al., 2000]. Others have argued that the demand for chemical inputs has been low because land is relatively abundant and farmers have little incentive to use cultivated land more intensively or to save on land costs [Binswanger and Pingali, 1988]. More recently, a renewed interest in policies inspired by Asian Green Revolution has emerged in Sub-Saharan African countries. This renewed optimism seems to be based on the assumption that rapid population growth on the continent will result in declining labor costs and growing land constraints [Nin-Pratt and McBride, 2014]. But as discussed by Woodhouse (2009) and despite rapid population growth, the performance of African agriculture is still largely limited by the high labor cost and low productivity of labor. This situation may again frustrate attempts to promote agricultural growth in Africa.

Standard economic models suppose that perfectly informed agent with time consistent preferences apply the optimal quantities of inputs and follow an optimized investment plan. Credit is often a prerequisite for the adoption of improved seeds and fertilizers and a farmer's ability to obtain credit may be correlated with land tenure and agricultural productivity itself. Credit can facilitate farm households in purchasing the needed agricultural inputs and hence enhance their capacity to effect long-term investment in their farms [Mohamed and Temu, 2008]. Specialized credit schemes are often established by the government to promote the adoption of specific agricultural technologies. Access to credit may raise allocative efficiency in agriculture. As Hazarika and Alwang (2003) argue a farmer unable to obtain market inputs in sufficient quantities may substitute non-market inputs such as labor of family members. However, given the opportunity cost of family labor, the farmer's input combination may be costlier than an alternative combination consisting of more purchased inputs and less family labor. Credit may allow the farmer to utilize market and non-market inputs in a cost-minimizing combination. Ultimately, the paper suggests that credit may also raise allocative efficiency by increasing a farmer's ability to bear risk and adopt more capital-intensive methods of production.

The encouragement of household saving is becoming a priority in the development agenda. Brune et al. (2013) tested access to savings accounts using a randomly selected sample of smallholder tobacco farmers in Malawi. They found that providing tobacco farmers with access to a saving accounts positively affected their savings level relative to the comparison group. Moreover, the group that opened a commitment savings account[20] saw a 17.1 percent increase in input use. Commitment mechanisms that bind individuals to future actions can overcome time inconsistency. However, people often underinvest, even in the absence of market failures or constraining social structures. The failure by smallholders to adopt productivity-enhancing input technologies may also result from low aspiration levels and mental models which downplay the role of investment. There are two possible points of views on this issue. Aspirations can also reflect the extent to which poor people feel that they have control over their future (i.e. underinvestment is a facet of low aspiration levels) [Bernard et al., 2012]. However, the poor might have low aspirations and weak orientation to the future because their own experiences suggest altering the condition of their poverty is difficult or impossible. The poor may lack the `capacity to aspire' which can be caused by poverty itself [Appadurai, 2004]. Personality traits might affect how agricultural inputs are used and adopted by smallholders other than productivity itself[21].

All decision-makers, either rich or poor, exhibit such mental models. However, poor people also suffer the psychological stresses of poverty and scarcity preventing them the understanding of opportunities they face. Bernard et al. (2014) showed short documentaries to smallholders in remote and rural part of Ethiopia. In these documentaries, people from similar backgrounds to the audience tell stories about their lives how they improved their socio-economic position. The authors showed that this intervention changed aspirations and saving behavior and led to increased investment in education.

Concrete information about opportunities will not always boost investment and learning behavior. People could fail to adjust on productivity frontier because they lack sufficient data to learn from. Even with sufficient information, there could be a failure to notice something in the data, as Hanna et al. (2012) noted when he talked about `learning through noticing'. In fact, agents can observe data during a demonstration that leads them to believe that they can use a technology profitably. Yet, when they adopt it, they systematically earn a negative surplus (disappointment) having ignored some dimensions necessary for effective use. Even relatively experienced agents may not understand the production functions that constrain their activities. Hanna et al. (2014) find that both experienced managers and farmers fail to recognize key inputs into their respective production functions. Moreover, production processes typically require a sustained effort over time, but agents may lack the self-control to exert effort now in order to earn rewards later [Kaur et al., 2015].

This chapter face the challenge to answer to some of the points raised with this introduction to the topic. Therefore, we want to understand whether behavioral traits help explain household decision to adopt and how

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[20] A commitment-saving account can force people to stick to a saving plan. They often mandate rules restricting individual choice in the future (accounts that charge per withdrawal, postponing the cashing of paychecks, giving money to a trusted individual to hold, opening an account at a branch that is inconveniently located, and choosing not to have an ATM card).

[21]There are two main branches of behavioral literature explaining individuals' deviations from profit-maximizing behavior. The first one holds that individuals have cognitive and time limits which limit the tractability of a decision problem. This is the concept of bounded rationality proposed by Simon (1955). Given that agents cannot consider all the possible combinations of choices available (i.e. the optimal choice predicted by neoclassical framework may be technically non-computable), individuals can analyze only partially the problem, ignoring infeasible strategies using heuristic mechanism to collect information, allowing them to choose that strategy which appears best given the information they have collected and their past experience in similar situations. The second approach, exemplified by Kahneman (2003), maintains that rational agents tend to avoid detailed analysis of choices and their outcomes due to the time and effort this would require. In fact, to process information is a time-consuming activity, because of this, agents recur to automatic thinking to get near optimal choice but which may lead to systematic biases in judgment.

much use particular inputs on their farm. The use of fertilizers and seeds may help raise the agricultural productivity and the livelihoods of the farmers.

The remainder of the chapter is organized as follows: section two sets out the empirical framework adopted. Section three reports the results for the allocative efficiency of inputs using non-cognitive skills. Section four, focuses on testing the recursivity hypothesis. Finally, section 5 concludes with policy implications of the analysis.

2.2. Allocative Efficiency of Agricultural Inputs: Framework

We have assumed that productivity Y is affected by inputs, household characteristics, and either cognitive/non-cognitive skills of household members working on the plot. As anticipated in the previous chapter, personality traits may affect performance on a task, controlling for cognition, other skills, and effort applied.

$$Y_i = f(V_i, X_i, B_i)$$

We can assess that the level of input adopted per plot by smallholders is in turn affected by household characteristics, and either cognitive/non-cognitive skills by positing

$$V_{ij} = g(X_i, B_i)$$

Smallholders' choices in the adoption of new input technologies to enhance agricultural productivity may also depend on their aspiration levels. Even with sufficient information smallholders may fail to apply inputs in appropriate quantities.

In the previous chapter, we examined how behavioral variables affect quantities produced conditional on input use. However, this is only part of the story since behavioral variables will also likely affect input choices. Indeed, this is what one should expect from standard neoclassical production theory in which agents equate the value of marginal factor products to input prices since the marginal product will depend on planned output. A decision to increase output will make it attractive to increase fertilizer application, for example. However, input use may also be affected by behavioral variables even in the absence of any impact on planned output. This could happen, for example, if a smallholder is reluctant to invest in fertilizers but aims to increase output by applying more household labor.

In the Zellner et al. (1966) model, input decisions predate harvest outcomes generating a recursive structure in which the errors on the input equations are independent of the production function error. It is this assumption that validates OLS estimation of the neoclassical production function. However, recursivity is undermined if common, unmodeled, behavioral variables enter both the input demand and output equations. Paradoxically, therefore, explicit modeling of the behavioral impacts on the input and output equations rescues the neoclassical Zellner et al. (1966) recursive strategy.

We model allocative efficiency using logit and ordered logit regressions for input use. We estimate the following equations:

$$D_i = \alpha_0 + \alpha_1' W_i + \alpha_2' X_i + \alpha_3' B_i + \nu_{i1} \quad (3)$$

$$S_i = \beta_0 + \beta_1' W_i + \beta_2' X_i + \beta_3' B_i + \nu_{i2} \quad (4)$$

Where D_j is a dummy variable equals one if a positive amount of **inorganic fertilizer** was applied on the plot j; S_j takes values one, two and three identifying the three terciles of **quantity of seeds applied** per hectare on the plot; X_i is a vector of household characteristics possibly affecting technical adoption; B_i is a vector of behavioral and personality variables relating to the household members working on farming plot j and ν_{i1} and

ν_{i2} are error terms. We estimate the equation (3) using a standard (binary) logit specification and equation (4) using an ordered logit.

2.3.Results

Results for equation (3) and (4) are shown in tables 1 and 2 in the appendix, respectively. In column (1) we estimated the models without behavioral measures, while we add them in column (2).

We start commenting the results for fertilizer use of Table 1 in the Appendix. Although we might expect that a higher quantity of inorganic fertilizer will be applied on low-quality soil, the efficiency of these inorganic fertilizers is typically low on depleted soils. Our results show that plots with low soil quality are negatively associated with the application of inorganic fertilizer but that, after controlling for soil quality, cultivated area is associated positively with the application of inorganic fertilizer. After introducing behavioral measures into estimation, some household characteristics lose statistical significance (household head age, dummy for being under extension service and having some system of irrigation on the plot) suggesting that these variables work to proxy omitted behavioral variables. The coefficient for number of bikes (to proxy household wealth) remains statistically significant and positive since behavioral variables are largely uncorrelated with wealth.

In table 1 we report average values of predicted probabilities to adopt inorganic fertilizers. We predict probabilities at fixed levels of noncognitive skills (lowest, median and highest scores). This sort of `simulation' allows us to analyze how propensity to adopt and use fertilizer may change according to different population's endowment of non-cognitive skills. We notice that being at the extremes of the distribution of non-cognitive skills (highest or lowest scores) is associated with a higher predicted probability of adopting inorganic fertilizer. To compare estimated impacts of personality traits with those of standard measures of human capital indicators (average education level of the household) we plot the predicted probability of adopting inorganic fertilizer on the plot for the distribution of average education level of the household, and the BFI and ER score distributions [Fig.2]. We hold all other covariates constant at the sample mean. We notice that both our measure of human capital (average education level in the household) and BFI scores to proxy non-cognitive skills display large confidence interval which only becomes thin near the median values of the distribution. The width of these bands this prevents us from drawing clear conclusions. Only predicted margins for ER scores show acceptable confidence bands. We notice a linear and increasing impact of higher levels of suppression scores on adoption of inorganic fertilizer. The reverse is true for the reappraisal facet. This implies that ER scores indicators better identify individuals most likely to adopt and disseminate new technologies.

Table 2 in the appendix shows results for the ordered logit model on quantity of seeds used. Again, the second column of the table reports the estimated coefficients associated with the personality traits. As with fertilizer application, the introduction of non-cognitive skills variables results in some household characteristics variables losing statistical significance.

The total cultivated area is positively associated with increasing quantity of seeds applied per plot per hectare. Looking at household characteristics, credit and the number of plows are important assets predicting seed use, while the coefficient household size (adult equivalents) is negative.

In the bottom part of table 1, we report average predicted probabilities estimated for the three terciles of quantity of seeds applied per hectare on the pot. Again, we estimated predicted probabilities fixing the values of non-cognitive skill scores. Having the highest attainable scores in all non-cognitive measures is associated with a higher probability of use a larger quantity of seeds per hectare, while the reverse is true when considering the margins predicted for the lowest scores.

Again, we compare predicted probabilities of adopting different quantities of seeds between human capital measure (average education level of the household) and non-cognitive skills measures. In this case, we distinguish between three different predicted probabilities: being in the first, second and third tercile of the distribution. Concerning average education level of the household, we notice a higher probability in using quantity of seeds associated with the second, first and third tercile, respectively. Increasing average number of years of education of the household cultivating the plot does not generate an increase in using seeds on the plot. We now look to non-cognitive skills measures. We focus our attention on extraversion, suppression and reappraisal scores. The marginal effect of increments in extraversion affects positively the probability of being in the second and the third tercile of seeds quantity distribution (with a greater steepness for the third tercile). While increments in the extraversion scores diminish the probability to use a small quantity of seeds per plot. The same pattern is observed for suppression score, even more accentuated. Concerning reappraisal, the variation is less prominent. Again, the ability of individuals to manage their emotions - especially the ability to suppress emotional reactions due to external shocks- appear to be relevant in identifying the most suitable farmers to adapt to new agricultural technologies.

From these results we can derive some sketched conclusions. First of all, standard measure of cognition such as the number of years of schooling in the family seems to be not relevant at explaining the choice to adopt certain inputs. The predicted probabilities graphs show no alteration as the education level increases or decreases. On the other hand, suppression and reappraisal traits well summarize the propensity of households to use fertilizers or more seeds on the plot. These results along with the average predicted probabilities at fixed values of non-cognitive skills show that highest scores are associated to higher probabilities. Therefore, acting on alleviating the external constraints that prevent households to use agricultural inputs may help to improve the psychological conditions for households to be receptive to new technologies and use them more effectively. How governments can act to modify such conditions? Some researches show that with small expedients is possible to boost the confidence and the compliance to certain behavior.

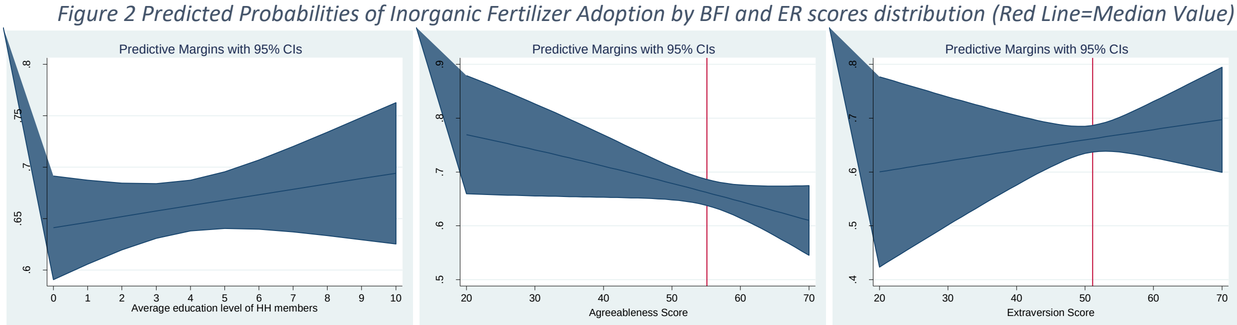
Table 1 Average Predicted Probabilities to adopt fertilizer/seeds fixed at Non-cognitive skills values Logit and Ordered Logit

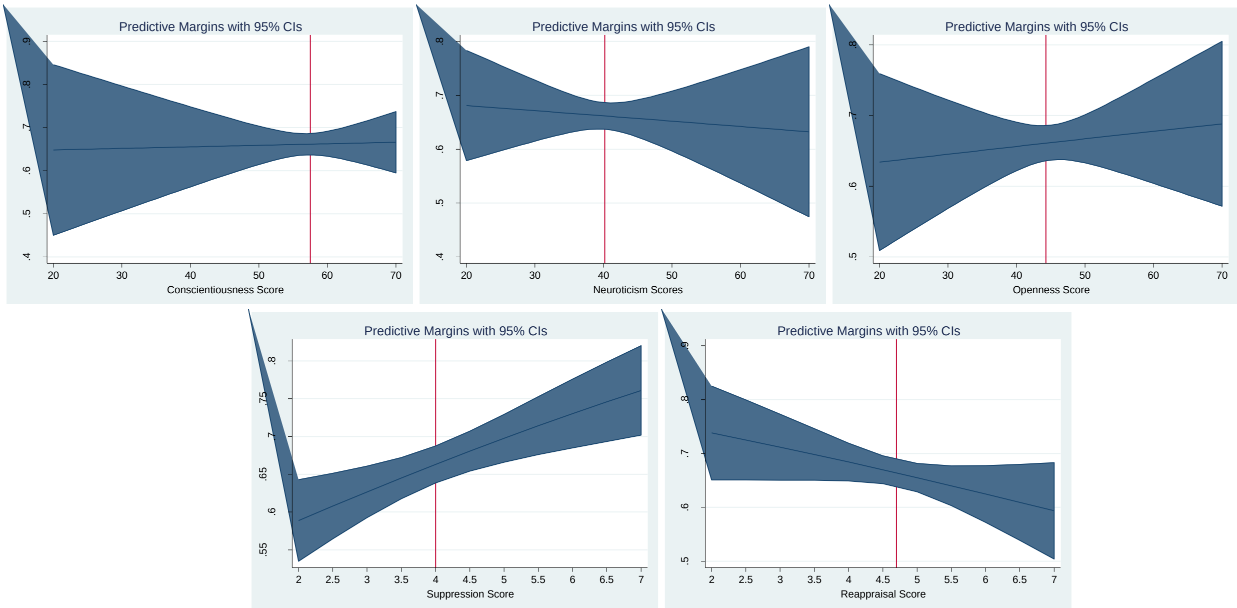
Logit Model (HH Charact+Non-Cognitive Skills) Fertilizers adoption		
(1)	**(2)**	**(3)**
Average Value Predicted Prob At NonCognitive Skills=**median values**	Average Value Predicted Prob At NonCognitive Skills=**lowest values**	Average Value Predicted Prob At NonCognitive Skills=**highest values**
.6668731*** (.012629)	.6956607*** (.094449)	.6951342*** (.0801368)

Ordered Logit Model (HH Charact+Non-Cognitive Skills) Quantity of Seeds used on the plot			
Predict	**(1)** Average Value Predicted Prob At NonCognitive Skills=**median values**	**(2)** Average Value Predicted Prob At NonCognitive Skills=**lowest values**	**(3)** Average Value Predicted Prob At NonCognitive Skills=**highest values**
First Tercile Seeds used	.3056443*** (.0126701)	.4335551*** (.0954654)	.160738*** (.0484879)
Second Tercile Seeds used	.5259597*** (.0150949)	.4679733*** (.0574894)	.5112607*** (.0336702)
Second Tercile Seeds used	.168396*** (.0116149)	.0984716*** (.0395403)	.3280013*** (.0783805)

Asterisks denote significance of coefficients: *** p<0.01, ** p<0.05, * p<0.1

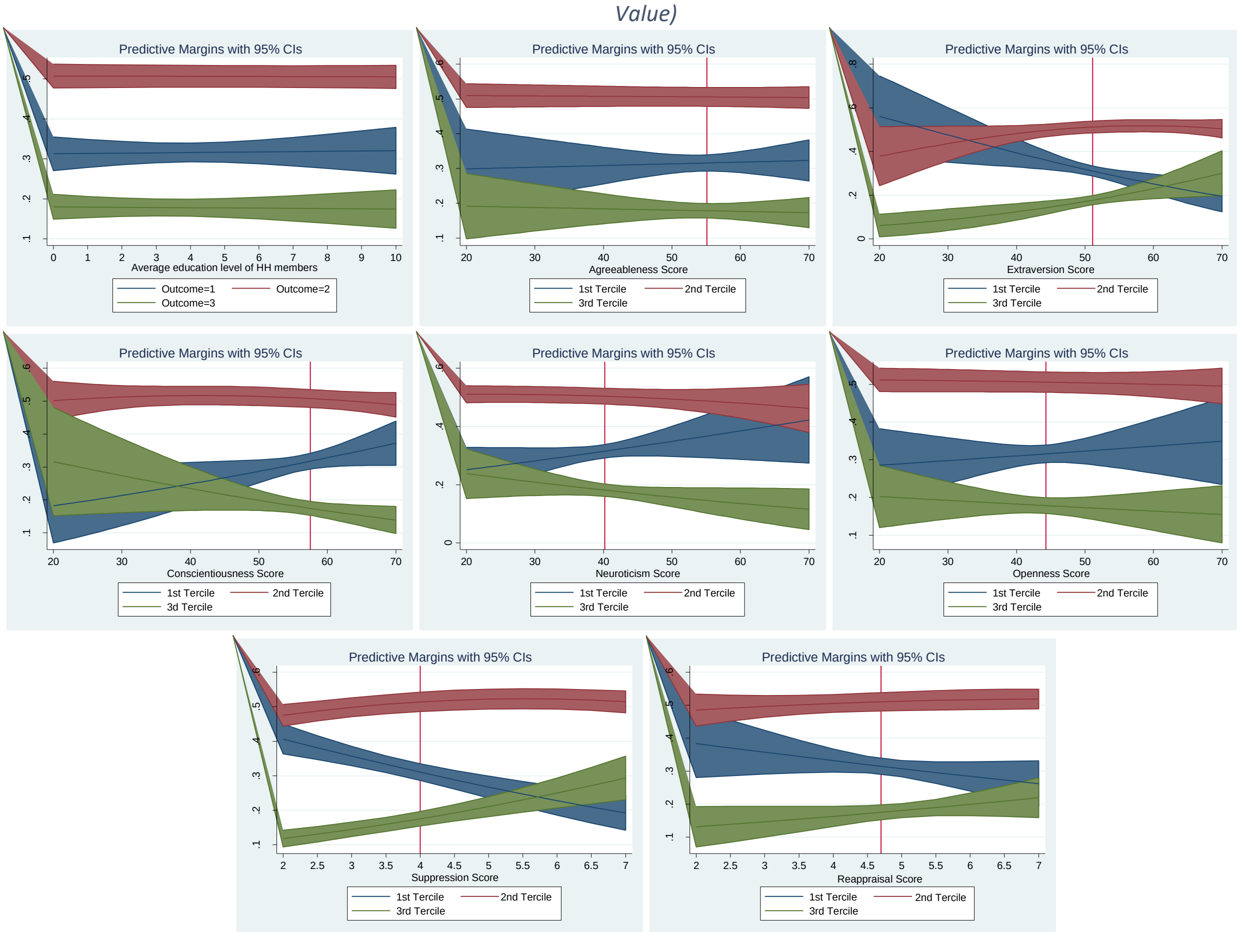
Figure 2 Predicted Probabilities of Inorganic Fertilizer Adoption by BFI and ER scores distribution (Red Line=Median Value)





BFI and ER scores of Family members working on the plot

Figure 3 Predicted Probabilities of Quantity of Seeds Applied per hectare on plot by BFI and ER scores distribution (Red Line=Median Value)



BFI and ER scores of Family members working on the plot

2.4.Testing the Recursivity Assumption

In this paragraph, we want to test the recursive structure between input decisions and production function. As previously mentioned, in the Zellner et al. (1966) model, input decisions predate harvest outcomes. Outputs, therefore, depend on inputs but inputs only depend on expected output. This validates OLS estimation of the neoclassical production function. However, recursivity is undermined if common, unmodeled, behavioral variables enter both the input demand and output equations. Therefore, by explicitly modeling the behavioral impacts on the input and output equations we can hope to rescue the neoclassical Zellner et al. (1966) recursive strategy.

In order to test this hypothesis, we recover residuals from the estimated Cobb-Douglas production function in the previous chapter. We define equations a_i and b_i as Cobb-Douglas production function without and with behavioral variables measures.

$$a_i = \ln Y_i = \delta_0 + \sum_{j=1}^{k} \beta_j \ln V_{ij} + \alpha_2' X_i + \delta' W_i + \epsilon_i$$

$$b_i = \ln Y_i = \delta_0 + \sum_{j=1}^{k} \beta_j \ln V_{ij} + \alpha_2' X_i + \alpha_3' B_i + \delta' W_i + \epsilon_i$$

$$\forall\, i = 1, \ldots, N$$

Then we recover the vector of residuals for both specifications $e_a = a_i - \widehat{a_i}$; $e_b = b_i - \widehat{b_i}$. Then we enter these residuals as an additional variable in the logit regression (equation 3) and ordered logit (equation 4) in case (a) with behavioral variables excluded and (b) included. In case the recursivity is confirmed we would expect the coefficient of the residuals to be statistically significant in the first case (e_a in the logit/ordered logit without behavioral variables) but insignificant in the other case. That is, when we omit behavioral variables in (a) error terms are correlated with output, but once the behavioral variables have been taken into account the error terms in the input decision and production function should be independent. We report results in Table 4. They weakly confirm out hypothesis: behavioral variables are not only important for econometric regression but as confirmed by Hausman test results in the previous chapter, they `contaminate' the estimated coefficients. In this case, we can weakly reject at 5% the recursivity assumption when introducing non-cognitive skills variables in the model.

For inorganic fertilizers, the coefficient of the residuals is significant at the 5% level in the "a" specification which omits the behavioral variables but is only significant at the 10% level in the "b" specification which includes the behavioral variables. Although the same direction of movement is apparent in the ordered logit equations for seed use, the coefficient remains significant at the 5% level in the "b" equations. In summary, these results confirm that, in the absence of behavioral variables, the errors in the production function and input use equations are correlated invalidating the standard recursive structure in which outputs are conditioned on factor inputs, but suggest that this structure can be at least to some extent rescued by modeling farmers' behavioral aspects.

Table 2 Recusivity: coefficients of residuals obtained from Cobb-Douglas specifications (e_a, e_b) inserted in the logit regression (column 1) and the ordered logit regression (column 2)

Coeff	**Inorganic Fertlizer (Logit)**	**Quantity of Seeds Used (Ordered Logit)**
e_a	0.1781**	-0.1859***
	2.16	-2.69
e_b	0.1795*	-0.1532**
	1.82	-2.10

*** p<0.01, ** p<0.05, * p<0.1

2.5. Conclusions and Policy Implications

These two chapters contribute to the current literature in extending the behavioral approach to the agricultural context in developing countries, providing two critics to the neoclassical economic framework. First, we assess that behavioral variables are not only important for the production function estimation but their inclusion alters the extent of the inputs coefficient. Second, we conditioned inputs choices on personality traits and we weakly confirm a recursive structure between inputs and output. In this section, we responded the previously mentioned issue of how non-cognitive skills affect smallholders' allocative efficiency (use a more or less efficient combination of inputs). This issue is strictly connected to the productive efficiency discussed in the previous chapter. The estimation of farm-level productivity is a well-known topic in the economic literature. However, there are various difficulties during the estimation. Zellner et al. (1966) were an early attempt to correct such problems in the estimation. The fact is that farmers observe idiosyncratic shocks and adjust their input choices accordingly. Moreover, the inclusion of non-cognitive skills might reduce bias to `unobservables' in empirical estimation making observable the unobservable variables that may affect household decision-making. This validates the Zellner et al. (1966) use of OLS to estimate the production function within a recursive structure in which the errors on the input equations are uncorrelated with those of the production function.

We are aware of the possible limitations of this analysis. First of all, a possible section bias of the sample may threat the external validity of the results we obtained. Second, as other researchers argued, the behavioral constructs we use to proxy non-cognitive skills may be hindered by mismeasurements and they may fail in capturing what they supposed to measure. Also, the use of cross-sectional data prevents us to use more advanced econometric tools to address other sources of endogeneity.

The failure by smallholders to adopt productivity-enhancing input technologies may also result from low aspiration levels and mental models which downplay the role of investment. This is in contrast with standard economic models which assume that perfectly informed agents with time consistent preferences chose how to apply the right quantity of inputs. That is, personality traits might affect how agricultural inputs are used and adopted by smallholders other than productivity itself. For example, Hanna et al. (2014) find that experienced managers and farmers respectively fail to recognize key inputs into their respective production functions. We address this second set of issues by estimating logit and ordered logit equations to investigate the role play non-cognitive skills in input adoption. The importance of including personality traits in the estimation is confirmed by the significance of the coefficients of the behavioral variables. Being at the extremes of the distribution of non-cognitive skills (highest or lowest scores) is associated with a higher probability of adopting inorganic fertilizer. Regarding the probability of using seeds per hectare having the highest attainable scores in all non-cognitive measures is associated with a higher probability of use a larger quantity of seeds per hectare, while the reverse is true when considering the margins predicted for lowest scores. Holding all other covariates constant at the sample mean we plot the predicted probability of adopting inorganic fertilizer and using different quantities of seeds on the plot for the distribution of the BFI and ER scores. Only the ER scores display predicted margins with acceptable confidence bands This implies that these behavioral measures better identify individuals most likely to adopt and disseminate new technologies. Concerning the probability of adopting inorganic fertilizer, we find a linear and increasing impact of higher levels of suppression scores, while the reverse is true for the reappraisal trait. Focusing on the probability to use a different amount of seeds, the marginal effect of increments in suppression and reappraisal scores positively affect the probability of being in the second and third terciles of seeds quantity distribution (with a greater steepness for the third tercile). Increments in the ER scores diminish the probability of using small quantities of seeds per plot. Concerning reappraisal, the variation along the distribution is less prominent. First of all, standard measure of cognition such as the number of years of schooling in the family seems to be not relevant at explaining the choice to adopt certain inputs. The predicted probabilities graphs show no alteration as the education level increases or decreases. On the other hand, suppression and reappraisal traits well summarize the propensity of households to use fertilizers or more seeds on the plot.

These results along with the average predicted probabilities at fixed values of non-cognitive skills show that highest scores are associated to higher probabilities. Also concerning the agricultural productivity, higher scores for conscientiousness, neuroticism, and suppression are all associated with a positive and statistically significant effect on agricultural productivity. Organizational skills, reliability, a strong capacity to "suppress" external emotional stimulus, and a high level of anxiety all appear to be yield-enhancing psychological characteristics. Therefore, acting on alleviating the external constraints that prevent households to use agricultural inputs may help to improve the psychological conditions for households to be receptive to new technologies and use them more effectively. How governments can act to modify such conditions? Some researches show that with small expedients is possible to boost the confidence and the compliance to certain behavior [see Bernard (2014) and Duflo's works].

In table 5 we provide a synthesis of the effect associated with BFI and ER measures we obtained from our empirical analysis.

These results may be useful in order to explain supply problems which have been widely cited to explain why some farmers do not purchase and use agricultural inputs. Incremental production from improved inputs usage is pointed as one of the priorities for boosting African agriculture. Our research suggests that the effects of subsidies and institutional innovation to overcome market failures and to increase input supply for farmers might be overstated by the literature. This judgment applies in particular, to studies comparing `average' versus `best' practices in inputs use within each country[22]. Simply increasing the availability of seeds and fertilizers may not translate in higher yields since other factors such as personality traits may concur to affect input adoption. It is difficult to see how policy-makers might alter those behavioral patterns which prevent farmers from reaching the technological frontier.

Faced with a lack of information regarding why and how people make their choices, one is left to assume a particular type of preferences and/or expectations. Provided enough care is taken to design attitudinal data, relevant analysis can be performed to usefully inform researchers about individuals' decision-making processes (Manski, 2004; Bernard et al., 2012). Viewed in this light, personality traits become a valuable analytical device for boosting agricultural productivity through inputs adoption. Non-cognitive skills can help answer why entrepreneurship appears to be limited in poor countries and help identifies what can be done to stimulate greater agricultural activity.

Moreover, these results can be useful for discussing the literature about poverty and the approaches to the problem. According to Dalton et al. (2010), the literature on poverty can be divided into two groups: the first, and most influential strand argues that poverty exists because to constraints that are external to individuals, such as credit, insurance market imperfections, coordination problems, governmental failures. The alternative view is that internal factors, such as the endowment of non-cognitive skills, aspiration and beliefs, are more likely to affect poorer individuals and influence their decisions that in a manner that tends to perpetuate poverty [Mojo and Fischer, 2015]. The two different approaches lead to two different kinds of policy responses: in the first case, policies aim to relax external constraints, while the second one justifies interventions that alter internal constraints as a means by which poor people could challenge and alter the conditions of their own poverty [Dalton et al. 2010].

The policy implications of the results obtained in these chapters could be assimilated to the second branch of literature, but a combination of the two approaches is definitely more indicated. Namely, all policies aiming

[22] The basic idea of Malmquist (1953) of the `frontier productivity approach' is to construct the best practice or frontier production function and to measure the distance of each country in the sample from the frontier using data envelopment analysis (DEA). The Malmquist approach can distinguish between two sources of productivity growth: changes in technical efficiency and technical change. The contemporaneous approach of Trueblood and Coggins (2003) identifies the best practice countries in each period and measure the change in each country's performance relative to the change in the frontier.

to address the external constraints could also play a role in addressing the internal constraints. This implies that when designing interventions to increase agricultural input adoption and/or improving yield productivity, should be taken into account the interaction with individual's beliefs, behavioral traits and other key factors affecting future-oriented behaviors. When considering personality traits as in our case arises an ethical problem. Government lacks the prerogative to alter personality change even though it could encourage early childhood development interventions that aim to support the development of non-cognitive skills. But even with the help of small initiatives undertook during the adulthood may bring to great improvements. As the findings of Bernard et al. (2014) suggest showing short documentaries to smallholders in remote and rural part of Ethiopia lead to an aspirations' change and saving behavior and a consequent increase in investment in education. Moreover, it would be discriminatory to target fertilizer supplies to those with the most conducive personalities. However, these findings might help in identifying individuals most likely to adopt certain technologies or to benefit from such adoption.

Concluding, the results highlighted in this paper confirm the relevance of behavioral approach in rural contexts such as Ethiopia, through the use of good measures of skills - whether cognitive of non-cognitive.

Table 3 Statistical Association between Agricultural Variables and Non-Cognitive measures (obtained from Regressions results, only statistically significant coefficients are reported)

Non-cognitive skills Measures	Definition	Yield Output (Cobb-Douglas)	Yield Output (Translog)	Inorganic Fertilizer Adoption	Quantity of Improved seeds per ha
Agreeableness	ability to cooperate in an unselfish way			Negative	
Extraversion	energy, positive emotions, assertiveness, sociability and the tendency to seek stimulation in the company of others, and talkativeness				Positive
Conscientiousness	organizational skills and the ability to act in a rational way	Positive			Negative
Neuroticism	the tendency to not control anxiety and stressful situations rationally	Positive	Positive		
Openness	the tendency to be open to new circumstances and unfamiliar intellectual experiences	Negative	Negative		
Suppression	defined as the ability to inhibit expressive behavior while emotionally aroused	Positive	Positive	Positive	Positive
Reappraisal	defined as the ability to interpreting potentially emotionally-relevant stimuli in unemotional terms				

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APPENDIX I

Table 1 Logit Regression: Using Inorganic Fertilizers on Plot

VARIABLES	(1) Woreda and HH Charact	(2) Woreda and HH Charact and Non-cogn Skills
Woreda (Lasta)	**-2.257*****	**-2.133*****
	[-7.519]	[-6.865]
Woreda (Sirba)	**-1.056*****	**-0.745****
	[-3.673]	[-2.287]
Woreda (Adele Keke)	-0.167	0.263
	[-0.538]	[0.689]
Woreda (Koro Degaga)	-0.332	-0.210
	[-1.027]	[-0.594]
Woreda (Turfe)	**-1.036*****	**-1.080*****
	[-3.050]	[-2.800]
Woreda (Basona Werana)	-0.435	0.135
	[-1.451]	[0.392]
Inputs		
Dummy for low quality soil	**-0.315****	**-0.416*****
	[-2.222]	[-2.576]
Log Crop Area Tot (ha)	**0.262****	**0.282****
	[2.399]	[2.329]
Household Characteristics		
Dummy for Female Household Head	0.00539	-0.206
	[0.0325]	[-1.070]
Household Head Age (years)	**-0.0206***	-0.0135
	[-1.900]	[-1.034]
Household Average Schooling	0.0166	0.0291
	[0.665]	[0.955]
Household Size per adult equivalent	0.0367	0.0597
	[0.789]	[1.167]
Dummy for Obtained Credit	0.218	0.186
	[1.574]	[1.185]
Number of Plough	0.0521	-0.0171
	[0.859]	[-0.199]
Number of Bike	**0.857****	**0.862***
	[2.155]	[1.906]
Dummy for Extension Services	**0.856*****	0.562
	[3.124]	[1.315]
Dummy for Irrigation System	**0.856***	0.300
	[1.738]	[0.361]
Big Five Inventory T-Scores (Family Members working on plot)		
Extraversion		0.0104
		[0.714]
Agreeableness		**-0.0188***
		[-1.701]
Conscientiousness		0.00193
		[0.133]
Neuroticism		-0.00529
		[-0.377]
Openness		0.00592
		[0.449]
Emotion Regulation Score (Family Members working on plot)		
Suppression		**0.196*****
		[3.100]
Reappraisal		-0.160
		[-1.633]
Constant	-0.314	0.618
	[-0.455]	[0.369]
Observations	1,393	1,167

*** p<0.01, ** p<0.05, * p<0.1
Robust Std Errors

Table 2 Ordered Logit Regression: quantity of seeds applied per hectare (terciles)

VARIABLES	(1) Woreda and HH Charact	(2) Woreda and HH Charact and Non-cogn Skills
Woreda (Lasta)	-0.119	-0.204
	[-0.521]	[-0.854]
Woreda (Sirba)	**0.404***	0.288
	[1.891]	[1.216]
Woreda (Adele Keke)	**1.256*****	**1.443*****
	[4.431]	[4.240]
Woreda (Koro Degaga)	0.121	-0.186
	[0.475]	[-0.644]
Woreda (Turfe)	-0.159	-0.218
	[-0.496]	[-0.622]
Woreda (Basona Werana)	**-2.041*****	**-1.860*****
	[-8.382]	[-6.825]
Inputs		
Dummy for low-quality soil	-0.0138	-0.143
	[-0.109]	[-1.050]
Log Crop Area Tot (ha)	**0.307*****	**0.357*****
	[3.120]	[3.459]
Household Characteristics		
Dummy for Female Household Head	**-0.299****	**-0.358****
	[-2.144]	[-2.306]
Household Head Age (years)	0.00321	0.00250
	[0.293]	[0.205]
Household Average Schooling	-0.0109	-0.00445
	[-0.481]	[-0.169]
Household Size per adult equivalent	**-0.0827***	**-0.136*****
	[-1.900]	[-2.949]
Dummy for Obtained Credit	**0.231***	**0.326****
	[1.915]	[2.354]
Number of Plough	**0.208*****	**0.260*****
	[3.424]	[3.345]
Number of Bikes	-0.269	-0.231
	[-0.892]	[-0.767]
Dummy for Extension Services	**0.881*****	0.361
	[3.584]	[1.028]
Dummy for Irrigation System	-0.480	-0.621
	[-1.131]	[-1.279]
Big Five Inventory T-Scores (Family Members working on plot)		
Extraversion		**0.0415*****
		[2.743]
Agreeableness		-0.00285
		[-0.285]
Conscientiousness		**-0.0241***
		[-1.926]
Neuroticism		-0.0197
		[-1.525]
Openness		-0.00737
		[-0.604]
Emotion Regulation Score (Family Members working on plot)		
Suppression		**0.256*****
		[4.864]
Reappraisal		0.139
		[1.456]
Constant Cut 1	-0.600	-0.444
	[-1.017]	[-0.347]
Constant Cut 2	**2.067*****	**2.343***
	[3.522]	[1.820]
Observations	1,393	1,167

*** p<0.01, ** p<0.05, * p<0.1
Robust Std Errors

Ethiopia: Non-farm Activities and Seasonality

Background:

Agriculture, Non-farm sector and Structural Transformation in Sub-Saharan Africa

Researchers and policy-makers have identified a range of bottlenecks causing economic stagnation in SSA countries. Many solutions and suggestions have been proposed to solve these problems over the post-independence period. Modernization of the agricultural sector remains the priority to promote economic development. As is evident from its high share in GDP, the agricultural sector heavily influences overall economic activity in SSA. Since the start of the new millennium, the rural non-farm sector has gained increasing importance, roughly 25% of rural full-time employment and 35–40% of rural incomes was attributed to the rural nonfarm economy in developing countries [Haggblade et al., 2002; van den Berg and Kumbi, 2006]. Nevertheless, little attention has been paid to the possible role of the rural non-farm sector in the process of structural adjustment and renewal of sustained economic development [Hamer, 1986].

Despite the vision of rural African economies as purely based on agriculture being outdated, the image continues to persist. Diversification of household income emerges naturally both from ex-ante risk management strategies and from ex-post coping with adverse shocks. Barrett et al., (2001) show that this paradigm applies in SSA. For the majority of households, participation in the non-farm economy is either part-time or seasonal and is largely motivated by the need to manage risk caused by uncertainties of weather, market price fluctuations and diseases affecting crops, livestock and family members [IFAD Rural Poverty Report, 2011]. It is often argued that African economies need to become less dependent on agriculture if they are to escape poverty. A `pessimistic' school of agricultural development specialists thinks that, for both technical and economic reasons, Africa cannot rely on agriculture as a source of growth or poverty reduction [Maxwell, 2004]. The existing literature offers only limited insights on how non-farm activities and income might contribute to the alleviation rural poverty [Loening et al., 2008]. Most poverty alleviation intervention strategies in Africa neglect rural entrepreneurship and tend to focus only on smallholder agriculture activity [Fox and Sohnesen, 2013].

The analysis is complicated both by definitional and methodological problems in assessing and comparing employment data in SSA. A variety of terms is used in the current literature to distinguish between different sources of rural income: ``off-farm'', ``non-farm'', and ``non-agricultural'' are examples of terms used[23]. Furthermore, information on the size and the economic significance of the SSA non-farm enterprise sector is imprecise and limited, with the vast majority of these activities operating in the informal sector.

The WB's *World Development Report* 2008 stressed that agriculture continues to be addressed as a fundamental instrument for sustainable development and poverty reduction. Agriculture contributes to

[23] In this chapter and the following ones, we adopt the definition of ``non-farm income'' which includes earnings deriving from rural non-farm entrepreneurship activities

development in many ways: as an economic activity; through a series of linkages[24] (as a source of growth for the national economy, a provider of investment opportunities for the private sector, and prime driver of agriculture-related industries); and as a livelihood (more than 80% of the decline in rural poverty is attributable to better conditions in rural areas rather than to out-migration of the poor) [World Bank, 2008]. The classical theory of agricultural transformation suggests that the share of agriculture in a country's labor force and total output should decline both in the cross-section and over time as income per capita increases. The economic literature has recognized that there is a strong link between agricultural and industrial growth. Agriculture can contribute to the growth of industrial sector by transferring the `surplus' of labor from agriculture to the industry with little or no reduction in the level of agricultural output. Some economists have argued that there is a point at which the marginal productivity of labor becomes almost zero in agriculture. If the population exceeds the quantity at which the marginal productivity of labor becomes zero, labor is available to the manufacturing sector without loss of agricultural output [Lewis, 1954; Ranis and Fei, 1961]. The basic cause and effect of the structural transformation are rising productivity of agricultural labor. Another main feature of structural transformation is a rising share of urban economic activity in industry and modern services. In rural areas of Sub-Saharan African countries, the relative reduction of the importance of agricultural and the expansion in rural non-farm activities are features of the process of economic development [Davis et al., 2014].

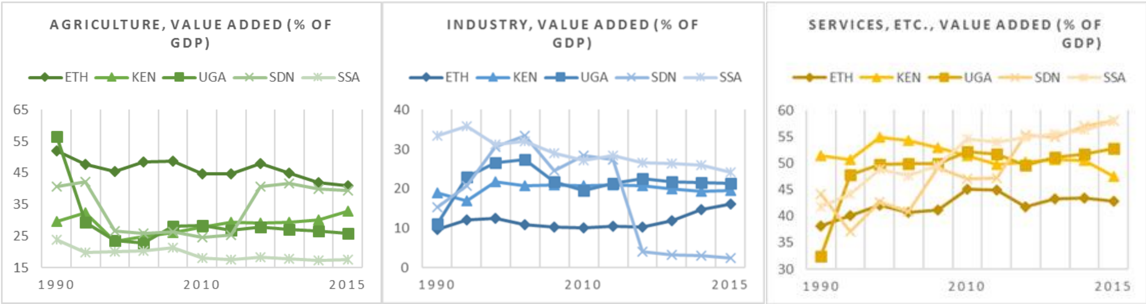
In addition, there are several other factors apart from agriculture, such as the process of urbanization and the national economic context, that may affect the form and development of non-farm enterprise activities. In particular, when the economic context is stagnant, opportunities for growth in the non-farm entrepreneurship activities are limited. After gaining independence in the 1960s African countries failed to achieve a structural transformation of their economies. Few African countries have yet achieved sustainable urban development. African urbanization is entering a critical phase at which the growth momentum presents an opportunity for accelerating national development and for creating the foundation of a sustainable urban future. Countries like Burundi, Rwanda, Malawi, Ethiopia and Burkina Faso are still overwhelmingly rural, whereas in Djibouti and Gabon more than 80 percent of the country's population lives in urban areas. Also, Nigeria experienced a rapid urbanization during the last year with almost half of its population living in urban areas [United Nations Economic Commission for Africa, ECOSOC, 2014]. The acceleration of growth of the industrial sector has been possible in those countries that could rely on the stability of their governments and on the administrative, legal and regulatory capacity to guide markets. Ghana and Kenya, with their progressive institutions, openness to civil society and media scrutiny, are among the countries pursuing the `good governance' route [Altenburg and Melia, 2014].

In the next paragraph, we provide a brief description of the economic performance of Ethiopia and neighboring countries (Kenya, Uganda and Sudan) focusing on those aspects likely to promote a favorable context for non-farm activities.

We find that Africa's economic structure is changing but at different speeds in each country. Figure one reports value added generated in three different sectors as a share of GDP for Ethiopia, Kenya, Uganda, Sudan and aggregated SSA countries (excluding high income). On average the share of services activities is growing in SSA countries. But after disaggregating the trends we notice that Ethiopia remains highly dependent on agricultural sector compared to its neighbors Uganda, Kenya and Sudan. The shares of industry and services have grown slightly over the most recent years, indicating that a structural transformation is taking place even though it is in its early stages. The inability to accelerate economic diversification away from agriculture keeps SSA countries vulnerable to external shocks and prevents the eradication of poverty.

[24] Haggblade et al. (2007) describe several linkages between agricultural and non-farm economy: production linkages, consumption linkages, factor market linkages, linkages between labor demand and rural/urban wage rates, and productivity linkages.

Figure 1 Sectors value added as share of GDP



Data from database: World Development Indicators

The embryonic stage of structural transformation of Ethiopia is also confirmed by the constraints and the struggle faced by households in the enterprise sector. Ethiopia has the highest bribery index amongst Uganda, Kenya and Sudan, as reported in Table 1. The time and the cost to start a new business also are respectively the longest and highest in the region. In conjunction with a low level of legal rights enforcement regarding credit, this results in major difficulties in starting and running businesses (as confirmed by the ease of doing business index). A coherent set of policies concerning human capital formation, infrastructure and institutions should be addressed to create stability and a favorable context for households to engage in non-farm enterprise activities. Concerning infrastructure, as Tagegne (2000) argues, there exist `truncated linkages' between rural and urban areas in Ethiopia, with the consequence of limited flows of agricultural commodities from rural to urban markets and in turn limited flows of manufactured and imported goods from urban to rural areas.

Table 1 Non-farm Sector in Africa

	Ethiopia (2015)	Uganda (2013)	Kenya (2013)	Sudan (2014)
Bribery Index (% of gift or informal payment requests during public transactions)	19.8	14.6	16.7	7.6
Days to obtain an Electrical Connection (upon application)	194.3	18.1	43.0	5.8
*Cost to get electricity (% of income per capita)	1414.9	13575.8	1081.3	4386.3
**Time required to start a business (days)	35	28	32	36.5
*Cost to start a business (% of income per capita)	79.1	78.3	38.2	25.1
Days to obtain an Operating License	5.4	10.4	13.8	4.7
**Start-up procedures to register a business (number)	14	13	7	11
Number of permanent full-time workers	36	15	43	25
Number of temporary workers	13	6	15	1
*Ease of doing business index (1=easiest to 185=most difficult)	159	116	113	164
*Credit: Strength of legal rights index (0=weak to 10=strong)	3	6	7	3

Source: World Bank Enterprise Surveys. *Source: World Bank Doing Business. **Source: World Development Indicators

- Ethiopia Economic Performance and Non-farm Entrepreneurship Activities

Evidence shows that close to 40% of African rural households are involved in non-farm activities despite the fact that only 9-19% of the rural labor force is employed in such activities [Haggblade et al., 2007]. Non-farm activities contribute between 8% (Malawi) and 36% (Niger) of average household income (World Bank, 2016). Based on a small number of case studies cited by Guenther et al. (2007) some 10% to 35% of rural households in Ethiopia may be engaged in nonfarm enterprise activities. Non-farm enterprises in Ethiopia are predominantly small with an average of employment of 1.14 workers [Ali and Peerlings, 2012]. Non-farm enterprises in Ethiopia appear to provide self-employment opportunities, yet very few wage labor opportunities.

Ethiopia is among the most populous countries in SSA, with a population of 97 million with continuing population growth. This only increases the need for income diversification strategies and promotion of non-farm enterprises activities. The latest Ethiopian five-year plan `Growth and Transformation Plan' (GTP) outlines an ambitious development strategy to transform the country from subsistence agriculture to become a highly-competitive industrialized economy by 2015 and a middle-income country by 2020 [UN-Habitat Report, 2014]. The GTP requires a variety of policies, specifically targeted financial support (subsidies and loans), state-owned corporations to address market failures, trade policies, tax incentives, investment in infrastructure, regulatory exemptions to attract foreign direct investment.

According to information obtained from the Addis Ababa City Administration, in 2004, 23% of young people between 15 and 20 years old were unemployed[25], and the rate is higher when considering people between 15 and 25 years of age. The `Addis Ababa Integrated Housing Programme' (AAIHDP) aimed to improve living standards of Addis residents through the creation of employment opportunities in small-scale and micro enterprises (SMEs).

Urban labor markets in Ethiopia are characterized by high unemployment and informality and the labor market position for youth, women and uneducated people is particularly disadvantaged. The situation is accentuated for women whose labor market position reflects their disadvantaged position in society: they carry most of the burden of domestic work, have lower educational achievements, are less likely to obtain a job, have longer unemployment spells, and suffer pay discrimination when they do manage to get a job [Rijkers, 2009].

According to Rijkers et al. (2008), non-farm activity in Ethiopia is predominantly a means to complement farm income rather than a pathway out of poverty. In addition, enterprise activity is highly countercyclical with agriculture, which suggests that non-farm enterprise activities are most appealing when the opportunity cost of labor is low.

Data

The `Living Standard Measurement Survey-Integrated Surveys on Agriculture' (LSMS-ISA) longitudinal data is a nationally representative panel of 3,776 households observed in 2011/12, 2013/14 and 2015/16 covering the regions of Tigray, Amhara, Oromya and Southern Nations, Nationalities and People's Region (SNNPR). The survey includes agriculture production information, participation into non-farm entrepreneurship sector, food consumption and household characteristics[26].

Information on the size and the economic significance of the Ethiopian non-farm enterprise sector is imprecise and limited. Most non-farm enterprises in Ethiopia are small and informal and offer no social

[25] The statistics on employment and unemployment were measured using ILO recommendation to use the strict definition of unemployment (``condition of people without work but willing to work who either carried out specific actions to find a job during the reference period''). However, during the data collection operation these international standards share the measurement problem that are common in countries with unorganized labor market and predominantly agrarian subsistent economy

[26] The sample for the first wave comprises 4,000 households in rural and small towns areas, the sample for the second wave was expanded to include 1,500 urban households, for a total of 5,500 households. The sample in the third wave comprises only households sampled in the first and second wave. Samples from all waves are a two-stage probability sample. The sample for the first wave is representative at the regional level for the most populous regions (Amhara, Oromiya, SNNP, and Tigray). In the second wave, in order to correspond with the existing first wave design while ensuring that all urban areas are included, the population frame was stratified to be able to provide population inferences for the same five domains as in the first wave plus an additional domain for the city of Addis Ababa.

protection. There is a lack of information about productivity levels and the survival and failure rates of these activities in Ethiopia as in other SSA countries.

In Table 2 we report main descriptive statistics of the sample disaggregated by year. On average 28% of households are female-headed with a family size of 4 people per adult equivalent. The dependency ratio (children less than 14 and elderly above 60 on labor age household members) averages 0.89. The level of schooling is quite low with an average household attainment of slightly less than 3.5 years. Half of the household heads cannot read or write. Farm size averages 1.25 hectares. Only 21% of the household had access to credit to buy agricultural inputs during last year, and only 16% of households reported to have access to a bank in the community. We see a general improvement in housing conditions along the three rounds. In fact, access to electricity tapped water source and flush toilet indicators improved from 2011 to 2016. The improved housing conditions reflected also on slightly improvements in malnutrition levels of children. On average anthropometric values are less than a standard deviation below the reference mean. During the 2015/16 round, an increasing number of households experienced several shocks such as damaged crop during the year, a drought or flood, an idiosyncratic shock or a price shock.

Table 2 Main Descriptive Statistics LSMS-ISA Ethiopia 2011/12, 2013/14 and 2015/16 rounds

Household Characteristics	**2011/12**	**N**	**2013/14**	**N**	**2015/16**	**N**	**Total**
Female HH Head	0.248	3969	0.304	5262	0.306	4887	0.286
HH Head can read and write	0.402	3905	0.494	5261	0.499	4887	0.465
HH Head Educ	2.697	3104	3.927	4525	3.747	4227	3.457
HH Head Age	43.1	3969	44.1	5262	46.4	4887	44.6
HH Size per AE	3.873	3969	4.069	5262	4.310	4887	4.084
Share of Children	0.489	3147	0.460	3933	0.502	4159	0.484
Share of Elderly	0.386	877	0.335	1211	0.293	1250	0.338
Share of Adult (Males)	0.318	3092	0.340	4252	0.293	3879	0.317
Share of Adult (Females)	0.319	3467	0.346	4633	0.300	4325	0.322
Dep Ratio (<15+>65)/(15-65)*100	8.97E-07	3785	7.09E-07	5123	1.07E-06	4739	8.92E-07
Rural Area =1	0.873	3969	0.609	5455	0.605	5329	0.696
Housing	**2011/12**	**N**	**2013/14**	**N**	**2015/16**	**N**	**Total**
Dummy for Electricity	0.179	3969	0.419	5262	0.402	4890	0.333
Dummy for Flush Toilet	0.019	3969	0.068	5262	0.107	4890	0.065
Dummy for Tapped Water Source	0.169	3969	0.408	5262	0.576	4890	0.384
Number of Rooms	1.661	3909	1.839	5258	1.914	4890	1.805
Farming Characteristics	**2011/12**	**N**	**2013/14**	**N**	**2015/16**	**N**	**Total**
Dummy for Irrigation System	0.114	2849	0.110	3173	0.108	3087	0.110
Crop Area (ha)	1.283	3118	1.312	3633	1.176	3664	1.257
Dummy for plot certificate	0.442	2649	0.468	3450	0.531	3460	0.481
Dummy for Improved Seeds	0.176	2791	0.189	3169	0.191	3085	0.185
Dummy fro Traditional Seed	0.974	2791	0.958	3169	0.988	3085	0.973
Shocks[27]	**2011/12**	**N**	**2013/14**	**N**	**2015/16**	**N**	**Total**
Dummy for Damaged Crop	0.673	2826	0. 600	3170	0.757	3111	0.676
Dummy for Geographic Shock	0.208	3969	0.102	5455	0.263	5329	0.191
Dummy for Idiosyncratic Shock	0.2045	3969	0.137	5455	0.285	5329	0.209
Dummy for Price Shock	0.291	3969	0.207	5455	0.305	5329	0.268
Dummy for Other Shock	0.022	3969	0.025	5196	0.014	4887	0.020
Dummy for Food Shock	0.285	3900	0.273	5244	0.247	4882	0.268
Food Consumption	**2011/12**	**N**	**2013/14**	**N**	**2015/16**	**N**	**Total**
Weekly Purchased Food Exp per ae*	3450.28	3900	1346.89	5200	71.44	4847	1622.87
Dummy for Poor Diet Variety	0.667	3969	0.662	5455	0.857	5329	0.728
Dummy for Critical Food Cons	0.515	3969	0.454	5455	0.498	5329	0.489

[27] Idiosyncratic shocks comprehend: if the household experienced the death, illness loss of a non-farm job of a family member; geographic shocks include: if a drought, a flood, a landslide/avalanche, or heavy rains occurred during the last year; price shocks refer whether a price fall or rise of a food item or of agricultural input occurred; food shock refer to lack of food in the household; other shocks include all other shock not included in the other categories.

Wealth	2011/12	N	2013/14	N	2015/16	N	Total
Dummy for Mobile Phone	0.293	3969	0.560	5455	0.606	5329	0.486
Gross Aggregate Agr Inc (BIRR)*	48921.90	3969	80553.36	5262	7329.63	4979	45601.63
Child Malnutrition	**2011/12**	**N**	**2013/14**	**N**	**2015/16**	**N**	**Total**
Stunting (height per age)	-1.430	2061	-0.593	2520	-0.582	2128	-0.869
Weight per age	-1.057	2061	-0.504	2520	-0.487	2128	-0.683
Wasting (weight per height)	-0.368	2061	-0.189	2520	-0.203	2128	-0.254
Body mass index zscore	-0.220	2061	-0.143	2520	-0.157	2128	-0.173

*2015/16 round values differ due to different survey construction

-Non-farm activities in Ethiopia: Descriptive Statistics

The LSMS-ISA data for Ethiopia shows that the percentage of household involved in some non-farm activity is around 28%. On average, households who engage in non-farm enterprise derive 25% of their cash income from these activities. Licenses grant individuals the right to operate a business in certain city or area and sector. The competent authorities check to make sure that the workplace is appropriate for the purpose and a registration is needed in order to collect taxes on sales and revenues. During 2016, less than 28% of rural non-farm enterprise had a license to formally operate and most operated from the household residence (36.2%).

Figure 2 shows that non-farm enterprises on average consist of just two workers (one of them being the employer). They rely almost completely on household labor (90% of the sample employ only family labor). The International Labor Organization (ILO) defines own-account work with contributing family workers as vulnerable statuses of employment. If the latter definition is applied, the vulnerable employment rate (sum of own-account and contributing family workers as a proportion of total employment) in this case is near unity.

Enterprises operates mostly in `buying and selling'/trade sector (38.6%); manufacturing (16.2%); transportation (15.2%); and electricity (12.4%). Agriculture represents the principal activity for households and processing food represent a consistent share of non-farm enterprises in the sample: on average 15%. This is consistent with the view of Ethiopian households being in the first stage of structural transformation where most of the entrepreneurship activities are directly linked to agriculture. Typically, they include the manufacture of fertilizer, agricultural and transport equipment. The second stage of transformation, non-farm activities are more varied focusing on tourism and services.

Local consumers and passers-by are the principal selling-base (40% of final selling). Most of the remaining sales are to markets (35%) and traders (18%) [Figure 3]. Figure 4 shows gender differences across enterprise sectors: typically women sell products[28].

On average, half of the non-farm activities are undertaken by female household members. The reason for the high participation of women in nonfarm employment reflects the cultural segregation of agricultural activity according to sex. For instance, many households in Amhara believe that the harvest will be bad if women work on the farm (Bardasi & Getahun, 2007; Zwede and Associates, 2002). According to Gellla and Tadele (2014), the `farmer' symbolic construction is an essentially a masculine cultural subject in Ethiopia with the plow occupying a pivotal and privileged place in the history of farming in the country. Women are seen as helpers and caretakers to the men who do the `real farming' due to this symbolic and somatic association. Men are traditionally responsible for plowing and cutting seed, while women traditionally perform weeding, preparing and carrying manure. They help with harvesting but are rarely are given the task of looking after cattle. As a result, it is difficult for unmarried women to be independent farmers since they have no opportunities to learn those activities and rely on non-farm activities as a primary source of income more likely than men [Gella and Tadele, 2014].

Female owned enterprises are on average smaller in size compared to men-owned ones, likely reflecting the unprivileged position of women in the Ethiopian labor market and enterprises run by female-headed

[28] These differences are statistically significant on average along the three rounds, t-test results are reported in table 3

households [Rijkers et al., 2008]. Often women are overrepresented in low-paid, household-based, labor-intensive activities because of the severe restrictions on their mobility (UNCTAD Report, 2015)

The primary sources of start-up capital are agricultural income, non-farm self-employment income and family and friends in the community. Only 8% of enterprises cited formal credit institutions (credit association, cooperative or bank loan, private moneylenders) as their primary source of funding. This suggests that informal entrepreneurs could possibly gain by formalizing the access to formal credit.

Self-reported constraints that prevent further growth of the non-farm businesses are access to the market (distance and cost), low demand for the goods and services produced and the difficulty of obtaining information on products in the market. For those enterprises with a formal license to operate, the major constraint is the high value of the taxes paid. Controlling for enterprises with licenses, we found no improvement in access to formal credit. Even though small entrepreneurs in Ethiopia have one of the highest rates of compliance for licenses amongst Sub-Saharan Africa [Nagler and Naudé, 2014], it still clear that disclosure of activities to the authorities is not perceived as advantageous or profitable. Compliance is a cost that is difficult to sustain. Taxation also imposes a compliance cost but there is the risk of being fined for operating without payment. Informal entrepreneurs could possibly gain by formalizing in terms of access to formal credit. Formalization would also entail compliance with a healthy and secure work environment for employees.

Figure 2 Frequency Distribution of the Number of Workers per Firm

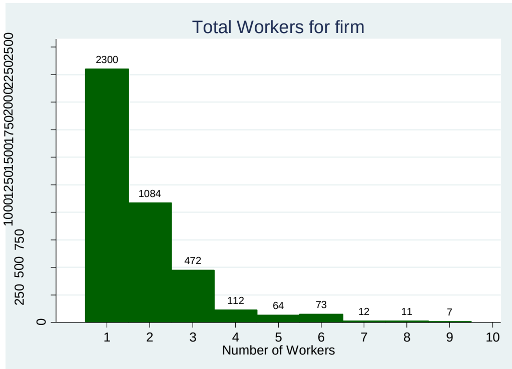


Figure 3 Main Selling Distribution

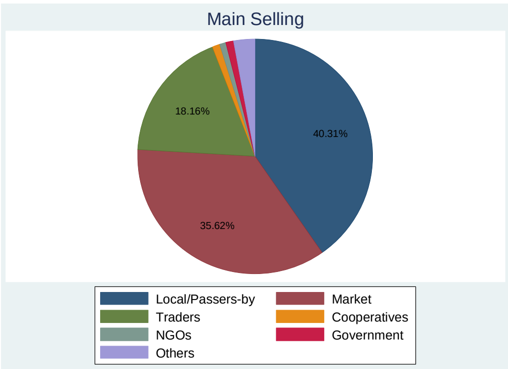


Figure 4 Sectors Distribution by Gender of Enterprise's Owner

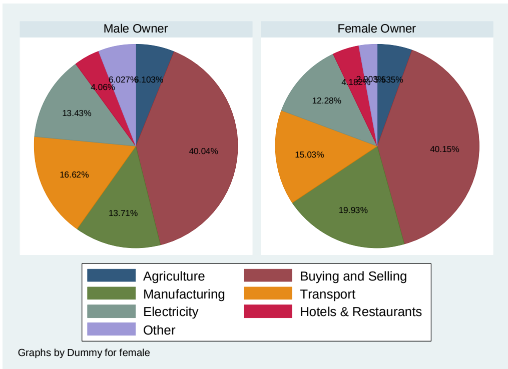


Table 3 Non-farm Characteristics: difference between female and male owners

	Male Owner	N	Female Owner	N	Total	Diff	
Agricultural Sector	0.059	4077	0.053	4216	0.056	0.005	
Buying/Selling Sector	0.385	4077	0.387	4216	0.386	-0.003	
Manufacturing Sector	0.132	4077	0.192	4216	0.162	**-0.060**	***
Transport Sector	0.160	4077	0.145	4216	0.152	**0.015**	*
Electricity Sector	0.129	4077	0.118	4216	0.124	0.011	
Hotel & Rest Sector	0.039	4077	0.040	4216	0.040	-0.001	
Other Sector	0.033	4077	0.020	4216	0.027	**0.013**	***
Tot Workers	1.787	4077	1.682	4216	1.735	**0.104**	*

House - Primary Operating Location	0.326	4077	0.413	4216	0.369	**-0.087**	***
Market - Primary Operating Location	0.358	4077	0.371	4216	0.364	-0.013	
Mobile - Primary Operating Location	0.117	4077	0.077	4216	0.097	**0.040**	***
Other - Primary Operating Location	0.198	4077	0.139	4216	0.169	**0.059**	***
Processed and sold any agricultural products (=1)	0.106	3429	0.199	3516	0.153	**-0.093**	***
Seasonal Activity (=1)	0.318	4055	0.314	4196	0.316	0.004	

Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1

We tested to see whether households that engage in non-farm activities are on average statistically different in household characteristics and farming activities from other households. Table 5 gives the results of t-tests that show that households with at least one non-farm enterprise are on average larger, with less educated and younger household head. Households with some non-farm activity on average experienced more shocks during the year (idiosyncratic and price), and have poorer access to water and flushed toilets while better access to electricity.

Looking at farming activities, the difference between the two samples is less evident: there is no statistically significant difference for the use of an irrigation system. Households with non-farm activities have less cultivated land but use more improved seeds.

We proxy wealth by the number of rooms in the dwelling and possession of a mobile cellphone. On this basis, households who do not participate in the non-farm sector are better off than those who participate but the difference is not statistically significant.

Since families with non-farm activities are larger due to a higher share of children, we examine if participating in the non-farm sector could increase health outcomes for children. Again, t-test results show that on average children living in families participating in the non-farm sector have inferior health outcomes.

We also investigate differences in food consumption indicators in table 5. Since there is no single way to measure food security, we adopted two indicators of household food consumption developed by World Food Program (WFP) and `Food and Nutrition Technical Assistance' (FANTA) project respectively. The first is the `Household Dietary Diversity Score' (HDDS) which measures the number of different food groups consumed over a given reference period. This is an attractive proxy indicator for food access. A more diversified diet is generally associated with a number of improved outcomes such as higher child birth weight, greater caloric and protein adequacy, a higher proportion of animal protein and higher household income. The second indicator is the `Food Consumption Score' (FCS) which measures the frequency of consumption of different food groups[29]. For each indicator is possible to calculate a threshold to assess a poor consumption/diet variety in the household[30]. Based on these measures, households participating in non-farm activities on average are more likely to have poor diet variety but are less critical with regard to food consumption. Table 5 shows percentages for FC and HDD scores.

[29] We calculate the HDDS counting how many different food groups household consumed, divided by household size per adult equivalent. The food groups are: cereals, root and tubers, vegetables, fruits, meat, eggs, pulse and legumes, milk and milk products, oil and fats, sugar and honey. FCS is calculated weighting the frequency of consumption of different food groups. The food groups are: main staple (weight 2); pulses (weight 3); vegetables (weight 1); fruit (weight 1); meat and fish (weight 4); milk (weight 4); sugar (weight 0.5); oil (weight 0.5); condiments (weight 0)

[30] The threshold for having a poor diet variety is set by the average HDDS for the first tercile of food consumption expenditure. For FCS a score below 28 is defined as poor food consumption, 28.5-42 borderline food consumption and above 42 as acceptable.

Table 4: t-tests results: testing statistically average difference between the two groups

Household Characteristics	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Female HH Head	0.294	9965	0.277	4153	0.285	**0.017**	**
HH Head can read and write	0.467	9903	0.478	4150	0.472	-0.011	
HH Head Educ	3.687	8242	3.206	3614	3.447	**0.481**	***
HH Head Age	45.1	9965	43.5	4153	44.3	**1.6**	***
HH Size per AE	3.983	9965	4.370	4153	4.177	**-0.387**	***
Share of Children	0.485	7780	0.481	3459	0.483	0.005	
Share of Elderly	0.348	2508	0.285	830	0.317	**0.063**	***
Share of Adult (Males)	0.323	7781	0.305	3442	0.314	**0.019**	***
Share of Adult (Females)	0.325	8610	0.316	3815	0.321	**0.009**	**
Dep Ratio (<15+>65)/(15-65)*100	0.886	9557	0.887	4090	0.887	-0.001	
Rural Area =1	0.670	10591	0.701	4162	0.685	**-0.032**	***
Housing	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Dummy for Electricity	0.341	9968	0.357	4153	0.349	**-0.015**	*
Dummy for Flush Toilet	0.071	9968	0.061	4153	0.066	**0.010**	**
Dummy for Tapped Water Source	0.406	9968	0.382	4153	0.394	**0.024**	***
Number of Rooms	1.785	9907	1.889	4150	1.837	**-0.104**	***
Farming Characteristics	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Dummy for Irrigation System	0.110	6275	0.111	2834	0.110	-0.001	
Crop Area (ha)	1.309	7081	1.143	3334	1.226	**0.166**	***
Dummy for plot certificate	0.503	6517	0.442	3042	0.473	**0.061**	***
Dummy for Improved Seeds	0.179	6011	0.198	3034	0.189	**-0.018**	**
Dummy fro Traditional Seed	0.975	6011	0.970	3034	0.972	0.005	
Shocks	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Dummy for Damaged Crop	0.682	6062	0.665	3045	0.673	0.017	
Dummy for Geographic Shock	0.187	10591	0.194	4162	0.190	-0.007	
Dummy for Idiosyncratic Shock	0.200	10591	0.230	4162	0.215	**-0.030**	***
Dummy for Price Shock	0.258	10591	0.282	4162	0.270	**-0.024**	***
Dummy for Other Shock	0.021	9914	0.019	4138	0.020	0.002	
Dummy for Food Shock	0.272	9886	0.257	4140	0.265	**0.014**	*
Food Consumption	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Weekly Purchased Food Exp per ae	1479.33	9819	1521.48	4128	1500.40	-42.15	
Dummy for Poor Diet Variety	0.703	10591	0.811	4162	0.757	**-0.108**	***
Dummy for Critical Food Cons	0.508	10591	0.432	4162	0.470	**0.076**	***
Wealth	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Dummy for Mobile Phone	0.501	10591	0.514	4162	0.508	-0.014	
Gross Aggregate Agr Inc (BIRR)	48696.63	10048	39700.45	4162	44198.54	8996.18	
Child Malnutrition	**Household Not Participating**	**N**	**Household Participating**	**N**	**Total**	**Diff**	
Stunting (height per age)	-0.865	4505	-0.810	2204	-0.837	-0.055	
Weight per age	-0.683	4505	-0.638	2204	-0.661	-0.045	
Wasting (weight per height)	-0.256	4505	-0.233	2204	-0.245	-0.023	
Body mass index zscore	-0.177	4505	-0.158	2204	-0.168	-0.019	

Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1

Table 5 Food Diversity and Food Consumption indices

Food Consumption Score		**Household Not Participating**	**Household Participating**
<28	*Poor Food Consumption*	25.29 %	18.44 %
28.5-42	*Borderline Food Consumption*	27.71 %	26.77 %
>42	*Acceptable Food Consumption*	47.00 %	54.79 %
Household Diet Diversity Score		**%**	**%**
Poor Diet Diversity		70.27 %	81.07 %
Not-Poor Diet Diversity		29.73 %	18.93 %

Descriptive statistics so far show that households involved in non-farm enterprises are generally poorer and have lower wellbeing. This is consistent with the view that these households are being pushed into non-farm activities rather than being attracted to them. These activities are much vulnerable employment modes, relying entirely on own-account and contributing family workers. Moreover, this is consistent also with the view that the poorest households have the greatest and strongest incentives to diversify into other activities, but they have the most limited capacities and opportunities to do so, limiting the benefits to them and to the wider economy. In fact, the pervasive level of engagement in the informal sector force often the insecure to low-paying part-time jobs. Usually, they remain the only option for many especially for poor people living in rural areas. To accelerate employment -especially for the youth- SSA countries must put stronger efforts to enhance the skills for the majority of young people -who missed out even on basic literacy skills- whose only option is in the informal sector.

- Linkages with Agriculture

In Figure 5 we plot months of activity of enterprises located in local and rural areas. During 2015/16, almost one-third of enterprises operate for five months or less, while in urban areas enterprises typically operate for the entire year. Along the three rounds, we notice that the percentage of households operating an enterprise for less of six months is shrinking in both rural and urban areas. The difference in economic opportunities between urban and rural areas shape household participation in the non-farm sector in different ways. Beyond urban areas, labor markets are typically characterized by an excess of supply of labor (except during the peak season) due to limited opportunities and factors pushing poorer households into seeking supplementary income [UNCTAD Report, 2015]. The months of greatest activity are reported in Figure 6. The highest activity is concentrated during the minor harvest season -Belg- September, October and November, and the first month of the dry season -Bega- December (45% of the sample reported December to be the highest month of enterprise activity).

In this sense, reported firm-activity seem to be counter-cyclical with respect to agricultural activity: with highest non-farm activity during the agricultural dry season, and the lowest activity during the main crop season –*Meher* - when heavy rains fall during June, July and August, and during the hottest month of the year May. This trend is confirmed controlling for the sector of activity and urban/rural location. Non-farm enterprise activity is much lower during the peak agricultural season, reflecting household labor allocation decisions to prioritize agriculture since most labor input is unpaid. Household decisions not to hire workers for enterprise activity suggest that supplying more labor is not worthwhile: the non-farm sector rather absorbs surplus labor in the household rather than `pulling' people away from agricultural activities. This is confirmed by the work of Haggblade, Hazell and Dorosh, (2007) and also by Ethiopian crop calendar for major crop foods on the right part of Figure 6. In addition, agricultural work during major crop seasons might be better paid because it is more demanding or because it is dominated by men, who tend to be better paid than women.

Figure 5 Months of Activity of Households' Enterprises

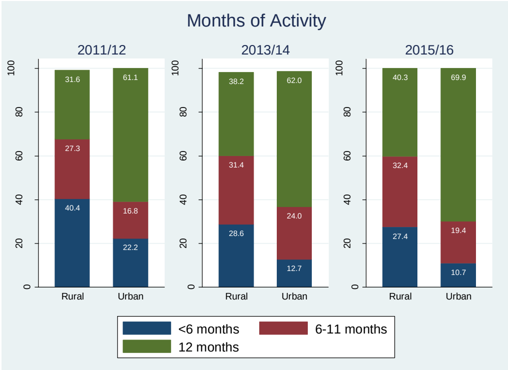
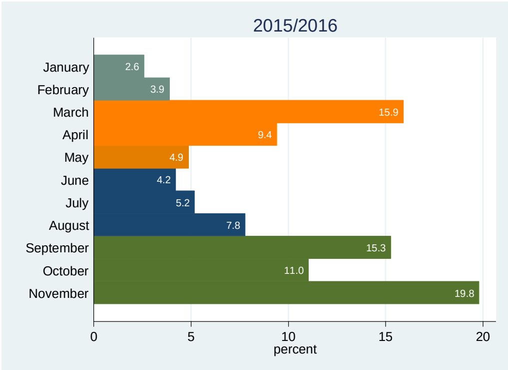
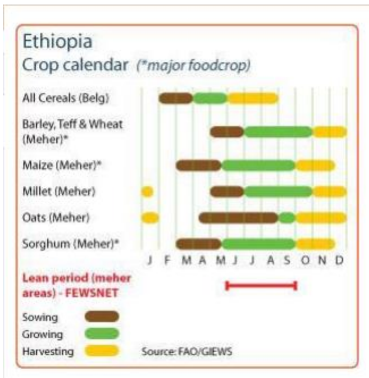


Figure 6 Enterprise highest activity during 2015/16. December is omitted because it accounts for almost 45% of the total





- Cluster Analysis

In this paragraph, we provide a brief cluster analysis focusing on the sample of households participating in the non-farm sector. We want to assess whether households with some enterprise activity can be grouped according to *push* and *pull* factors variables: `push' factors comprise shocks, any surplus of household labor and seasonality while, `pull' factors related to educational attainment, household wealth and the availability of business opportunities at a distance from the nearest large town. We restricted the sample to the households having at least one non-farm activity, about 4,000 observations (1,077, 1,584 and 1,501 amongst the three rounds). We perform a hierarchical agglomerative method proposed by Ward (1963) where groups of observations are joined to maximize an objective function. The agglomerative hierarchical clustering methods begin with each observation's being considered as a separate group and then the closest two groups are combined[31]. We restrict the set of variables to push (household size per adult equivalent, rainfall, shocks, cultivated area) and to pull factors (household head age and literacy, proxy for wellbeing, distance from market and road) and other household characteristics (female household head) and regional variables (rural areas, and woreda district).

Figure 7 reports the dendrogram (also called cluster tree) for the hierarchical clustering we performed. The dendrogram graphically presents the information concerning which observations are grouped together at the various levels of similarity. The highest is the branch the strongest is the clustering of the observations. The dendrogram indicates the presence of three major groups (G1 the first group, G2 the second and finally G3 the last one). Looking at the mean values of the variables for the three groups we set out to classify the groups according to the prevalence of push or pull factors [Table 6].

On average the first group could be defined as the `push' factor-group, with the greater mean values for household size and experienced shocks. Also, this group is characterized by higher level of wealth (possession of a plow, a larger number of rooms). We can identify this group as the most involved in agriculture and with

[31] We provide a brief technical appendix after this paragraph explaining the methodology

the largest area of cultivated land. We identify the second group as that in which `pull' factors prevail. It is characterized by the lowest values for experiencing a shock during the year, the youngest and the most literate household heads, but also by the farthest distances from the market and the main road. The last group is mainly characterized by push factors, but also by the rural location, and having a female household head. This last group is the most severed pushed group in the non-farm sector: with the most disadvantaged segment of the population -rural female-headed households- subject to highest probability to experience lack of food, idiosyncratic, price and other shocks during the year.

Figure 7 Dendrogram for Ward's Cluster Analysis

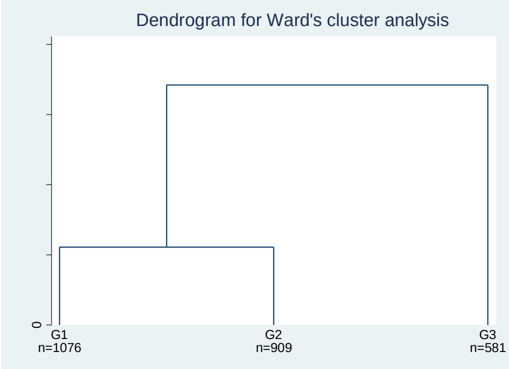


Table 6 Descriptive Statistics for Cluster Groups

	Group 1		Group 2		Group 3	
VARIABLES	mean	N	mean	N	mean	N
Rural Area (=1)	0.901	1,076	0.869	909	**0.910**	581
Female HH Head	0.222	1,076	0.187	909	**0.315**	581
Push Factors						
HH Size per AE	**5.438**	1,076	3.588	909	4.436	581
Rain during major season right amount (=1)	**0.453**	1,076	0.439	909	0.444	581
Food Shock (=1)	0.308	1,076	0.283	909	**0.324**	581
Geog Shock (=1)	**0.238**	1,076	0.163	909	**0.238**	581
Other Shock (=1)	**0.0204**	1,076	0.0165	909	0.0189	581
Idiosync Shock (=1)	0.230	1,076	0.168	909	**0.246**	581
Price Shock (=1)	0.316	1,076	0.241	909	**0.263**	581
Crop Damage (=1)	**0.679**	1,076	0.647	909	0.654	581
Cultivated Area (ha)	**1.418**	1,076	1.055	909	1.296	581
Pull Factors						
HH Head age (years)	44.79	1,076	**29.91**	909	65.56	581
HH Head can read (=1)	0.414	1,076	**0.416**	909	0.355	581
Bank (=1)	0.0623	1,076	**0.0858**	909	0.0585	581
Number of Rooms	**1.853**	1,076	1.650	909	1.795	581
Plough (=1)	**0.586**	1,076	0.505	909	0.527	581
Log Distance from Market	**3.543**	1,076	3.675	909	3.555	581
Log Distance from Road	**2.144**	1,076	2.146	909	2.096	581
Number of total hh_id		2,870		2,870		2,870

Concluding, the clustering of households engaging in the non-farm sector results in three major groups. In fact, looking at mean values of the variables associated with push factors we assess whether the group is prevalently characterized by those factors. The third group, as shown by the dendrogram, is the most dissimilar: this is due to the highest percentage of female household heads and households located in rural areas. The group summarizes the characteristics of the most disadvantaged sector of the population who diversify their income.

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3.Non-farm Entrepreneurship Activity in Ethiopia: Determinants and Impacts on Household' Wellbeing

3.1. Introduction

Reduction of rural poverty in Africa over the next 50 years depends on achieving massive production improvements and increases in labor productivity. For the most part, poverty alleviation policies focus primarily only on smallholder agricultural activity. The vision of rural Africa economies as purely based on agriculture is outdated, but the image persists even today. However, it is arguable that reduction in rural poverty may depend more on what happens off-farm than on-farm. Evidence shows that close to 40% of African rural households are involved in non-farm activities despite the fact that only 9-19% of the rural labor force is employed in such activities [Haggblade et al., 2007].

According to Rijkers et al. (2008), non-farm activity in Ethiopia is predominantly a means to complement farm income rather than a pathway out of poverty. This is consistent with results obtained in the previous chapter: t-test results showed that households with at least one non-farm enterprise are on average larger, with less educated and younger household head. Households with some non-farm activity on average experienced more shocks during the year (idiosyncratic and price ones), and have poorer access to water and flushed toilets while better access to electricity. Descriptive statistics so far show that households involved in non-farm enterprises are generally poorer and have lower wellbeing. Also cluster analysis shows that households split into three major groups: one where on average push- factors prevail, the second where prevail pull-factors, and the third one as the most dissimilar due to the higher percentage of rural female-headed households.

We use the LSMS-ISA data for Ethiopia to address two questions: a) What are the major determinants of households' participation in the non-farm sector (`push' or `pull' factors)? b) Does participation in these activities positively affects indicators of household well-being (such as food consumption and variety). We assess how non-farm earnings derived from non-farm activities affect household wellbeing as evidenced in food consumption and household food security. These are crucial in Ethiopia given its dependence on agriculture, exposing households to both seasonal price variability and food price volatility. An enhanced understanding of the influence of non-farm income can inform food security policy and initiatives.

Our results confirm that households are more likely to have a rural non-farm activity as the result of push factors than because of remunerative business opportunities. This is consistent with the view that these households are being pushed into non-farm activities rather than being attracted to them. These activities are much vulnerable employment modes, relying entirely on own-account and contributing family workers. Moreover, this is consistent also with the view that the poorest households have the greatest and strongest incentives to diversify into other activities, but they have the most limited capacities and opportunities to do so, limiting the benefits to them and to the wider economy. Moreover, female household heads are more likely to start a non-farm activity though this is typically at a small size, possibly reflecting gender-based cultural segregation of agricultural activities. For instance, many households in Amhara believe that the harvest will be bad if women work on the farm (Bardasi & Getahun, 2007; Zwede and Associates, 2002).

Looking at the non-farm sector we find that participation has a stronger impact on food security indicators than on household food consumption expenditure. Empirical evidence suggests a positive correlation between non-farm income and wealth indicators although the causation could run in either direction. For example, households with diversified income may potentially have a better nutritional status and greater food security, augmenting the share of food in total consumption. Moreover, non-farm income might improve agriculture performance providing farmers with cash to invest in agricultural inputs [Babatunde and Qaim 2010; Sani et al., 2014; Woldeyohanes et al., 2015].

The body of the chapter is organized as follows. Section 2 briefly present the theoretical background. In section 3 we outline the empirical strategy and report the estimation results. The final section concludes.

3.2. Theoretical Background

Becker's (1965) seminal study was the first one to formalize the concept of household time allocation choices. The study provided the theoretical framework to further develop a class of models of household time allocation choices. Time is an important resource in a developing country context where the economic agent's (individual or household) interaction with the outside world (through market activities) is relatively more restricted than in developed countries. Like any other resource in the household, time is not equally distributed across members. There are significant differences not just along gender lines but also by age, social status and wealth to cite the most relevant. Also, time use is not constant over the cycle of the year especially in rural areas. Time allocation is found to be largely affected by seasonality, for example winter is usually characterized by a low engagement in agricultural activities on-farm, while during the peaks of the agricultural season it involves larger amounts of labour (Ilahi, 2000).

The main assumption in the Becker model and its extension is that households seek to maximise the household utility function defined over consumption commodities and that time is allocated between work and leisure so as to maximise that utility function. We draw upon the economic theory of farm households (Singh et al. 1986) and empirical studies of household labour allocation in developing countries (Rosenzweig, 1980; Jacoby, 1993; Abdulai and Delgado 1999) to provide a basic theoretical framework for the determinants of household time allocation in multiple sectors. The theoretical framework here presented ignores all the complexities of the model and eventual extensions.

We assume that each household maximizes its utility U which is a function of consumption $\boldsymbol{C}$ and leisure time L (equation 1). Household consumes both food (c_f) and manufactured goods (c_m) We also assume that household and individual characteristics (Z) influence preferences. The household production function on the farm is defined as $Q(l^{AGR}, \boldsymbol{z}, F)$, where l^{AGR}in on-farm labor, $\boldsymbol{z}$ is a vector of variables inputs such as fertilizer, and F is a vector of structural characteristics of the farm. The labor market failure is described as the off-farm labor constraint $l^{NAGR} \leq \dot{l^{NAGR}}$ where $\dot{l^{NAGR}}$ is the maximum hours farmers can work off the farm.

Utility is maximized over a time constraint equation (2) and a cash income constraint equation (3) where we include income derived from household farm production and incomes and from non-agricultural activities (w^{NAGR}).

$$\max_{C} U = f(\boldsymbol{C}, L; Z) \tag{1}$$

$$T = L + l^{AGR} + l^{NAGR} \tag{2}$$

$$pQ(l^{AGR}, \boldsymbol{z}, F) - p_z z + w^{NAGR} l^{NAGR} + V = \boldsymbol{C} \tag{3}$$

$$l^{NAGR}, l^{AGR} \geq 0; \; l^{NAGR} + l^{AGR} = 0 \tag{4}$$

Where p is the farm output price, p_z is the input price, w^{NAGR} is the off-farm wage, and V represents transfers. The first order condition for this problem are:

$$w^{AGR*} = p \frac{\partial Q}{\partial l^{AGR}} = w^{NAGR} \quad if \quad l^{NAGR} > 0 \tag{5}$$

$$w^{AGR*} = p\frac{\partial Q}{\partial l^{AGR}} < w^{NAGR} \quad if \quad l^{NAGR} = 0 \tag{6}$$

$$w^{AGR*} = p\frac{\partial Q}{\partial l^{AGR}} > w^{NAGR} \quad if \quad l^{AGR} = 0 \tag{7}$$

w^{AGR*} is called the shadow wage or the opportunity cost of time. If the constraint on off-farm work is not binding then the return from farm and off-farm work should be equal to the shadow wage (equation 5). Otherwise, if the constraint is binding than the return from farm work can be set to the shadow wage but less than the off-farm wage (equation 6). Substituting the shadow wage into the budget constraint we can find the optimal labor supply. Farm households will develop different labor participation strategies according to their asset position and to the relationship between hired wage rate, off-farm market wage rate and shadow wage.

However, within this empirical application is taken to be equal to the observed off-farm wage (w^{NAGR}). We derive the labor supply solving the maximization problem. This is reasonable provided there are no transaction costs (transportation etc.) involved in non-agricultural work. It follows that $w^{AGR} = pQ(l^{AGR}, \boldsymbol{z}, F) - p_z z$.

Equation (8) shows the determinants of time allocation in different activities: wage levels (w^{AGR} and w^{NAGR}), capital (K), infrastructure conditions (IN), household characteristics and time. We group these determinants for the following empirical analysis in two broad categories: *PUSH* and *PULL* factors.

$$\left.\begin{matrix} l^{NAGR} \\ l^{AGR} \end{matrix}\right\} = g\ (w^{NAGR}, w^{AGR}, K, IN, Z, T) \tag{8}$$
$$= g\ (PUSH, PULL)$$

We can summarize push factors as those factors which determine the agricultural shadow wage. They come through the farm production function. Pull factors are those that come through the non-agricultural wage. There may be important costs in engaging in off-farm work, this third set may be a crucial "wedge" between the agricultural and non-agricultural wages.

3.3. Empirical Strategy

In this section, we investigate the probability that the household to participate in a non-farm enterprise activity focusing on whether push or pull factors predominate. Based on this first set of results, we analyze the impact of non-farm earnings on household wellbeing, specifically food consumption, quality of food consumed and agricultural technology adoption. The evidence in the current literature suggests mixed conclusions about how non-farm income contributes to food security and household food consumption: the nutrition impacts may be positive because non-farm income contributes to higher household income and better access to food, but could be also negative since working off-farm could reduce household food availability due to competition for family labor between farm and non-farm work. Moreover, non-farm income might improve agriculture performance providing farmers with cash to invest in agricultural inputs [Savadogoa, Reardonb and Pietolac, 1998; Diiro and Sam, 2015; Anang, 2017].

In order to answer the first question, we analyze the main contributions to household participation in the non-farm sector. We run a fixed effects (FE) logit regression using the longitudinal structure of the data to identify household and location characteristics that might determine the decision of a household to operate a non-farm enterprise. With a panel data structure, we can use the subjects as their own controls. We can control for stable characteristics that do not change over time (i.e. only the constant heterogeneity). FE models look at the determinants of within-subject variability: if there is no variability within a subject over time there is nothing to examine. Therefore, some heterogeneity still remains.

The estimating equation is the following:

$$PR(L_{it} = 1) = \frac{\exp(\alpha_i + X_{1it}\beta_1 + X_{2it}\beta_2)}{1 + \exp(\alpha_i + X_{1it}\beta_1 + X_{2it}\beta_2)}$$

$$t = 1,2,3 \qquad i = 1, \dots, N$$

Where L is a binary variable indicating participation in the non-farm sector, and X_{it} is a vector of household and location characteristics. X_1 refers to push factors (household size and dependency ratio, shocks, cultivated area and amount of annual precipitation) and X_2 to pull factors (literacy, number of rooms and owning plough and mobile phone used to proxy wealth, distance to main road and market, having a bank in the community), α_i is the fixed effect. Information on wages (minimum wage in the urban center, average wage o the nearest cities) are often included as pertinent push-related variables. Unfortunately, the survey does not collect information on wages. Using wage levels derived from the data could be an additional source of endogeneity[32]. For these reasons we are unable to control for the attraction of urban wages toward rural households. The same reasoning applies to the decision to not include variables concerning migration behavior within the household. Since the direction of causality is not well defined (households can afford to send a family member away because already participate into non-farm activities or the opposite?). Table 2 reports averaged marginal effects for the entire sample and on the sub-sample of rural households.

Table 2 Logit Regression FE: the probability of having a non-farm activity. Averaged marginal effects

VARIABLES	(1) FE Logit	(2) FE Logit -Rural-
Female HH Head	.0522	.0827
	[1.10]	[1.55]
Push Factors		
HH Size per AE	**.0186***	**.0221****
	[1.84]	[1.98]
Rain during major season right amount (=1)	.0211	.0166
	[1.24]	[0.91]
Food Shock (=1)	-.0007	.0093
	[-0.04]	[0.47]
Geog Shock (=1)	-.0382	-.0366
	[-1.47]	[-1.34]
Other Shock (=1)	**-.1696****	**-.1857**
	[-1.97]	[-2.11]
Idiosyncratic Shock (=1)	**.0473****	**.0483***
	[1.99]	[1.93]
Price Shock (=1)	**.0409***	**.0473***
	[1.85]	[1.94]
Crop Damage (=1)	**.0326***	**.0404***
	[1.69]	[1.87]
Log Crop Area (ha)	**-.0146****	-.0092
	[-2.03]	[-1.34]
Pull Factors		
HH Head age (years)	-.0017	-.0025
	[-0.88]	[-1.11]
HH Head can read (=1)	**.0345***	**.0450****
	[1.76]	[2.01]
Bank (=1)	-.0052	.0626
	[-0.07]	[0.81]
Number of Rooms	.0124	.0069
	[1.05]	[0.53]
Plough (=1)	-.0055	-.0153
	[-0.23]	[-0.59]
Log Distance from Road	**.0125***	.0181**
	[1.74]	[2.11]
Log Distance from Market	.0040	.0004
	[0.46]	[0.04]

[32] We also try to proxy the level of development of the urban centers using national-level luminosity data for Ethiopia. However, given the low degree of urbanization of the country the data do not help proxy urban centers. We do not include results in the text.

2014	**.2059*** **	**.2365*** **
	[2.92]	[3.10]
2016	-.0443	-.0536
	[-1.44]	[-1.59]
Observations	3,014	2,938
Number of hh_id	1,184	1,150

*** p<0.01, ** p<0.05, * p<0.1
Clustered Std Errors at region level

The probability that a household has a non-farm activity is positively associated with push factors as household size per adult equivalent (so a surplus of labor in the household) and shocks (idiosyncratic, crop damage and price shock) and negatively with other shocks. Focusing on the pull variables, only the literacy of household heads is positively and statistically significantly associated with a higher probability of doing business. Other variables accounting for pull factors are not significant or do not have the expected sign. This is the case with distance from the main road which has a statistically significant positive coefficient the reason could be that households face less organized competition in remote areas[33].

To understand the impact of non-farm earnings on household food consumption we now report estimates of a Heckman selection model following the methodology proposed by Wooldridge (1995) for panel data. As mentioned beforehand, the FE logit model control for the constant heterogeneity across time. This method allows for the possibility that explanatory variables are not strictly exogenous even after we remove the unobserved effect with standard FE model. In our case the choice to participate in non-farm activities. FE models allow the selection to be correlated with the unobserved heterogeneity returning biased estimates. We formulate the following model:

$$Y_{it}^{*} = X_{it}'\beta + \mu_i + \xi_t + \epsilon_{it} \quad (1)$$

$$d_{it}^{*} = Z_{it}'\gamma + \alpha_i + \psi_t + \nu_{it} \quad (2)$$

$$d_{it} = 1 \; if \; d_{it}^{*} > 0$$

$$Y_{it} = Y_{it}^{*} d_{it}$$

$$t = 1,2,3 \qquad i = 1, \dots, N$$

Where Y_{it}^{*} and d_{it}^{*} are latent variables, a consumption indicator and a household non-farm participation dummy respectively; X_{it} and Z_{it} are two sets of covariates affecting Y_{it}^{*} and d_{it}^{*}. They contain both household characteristics, information on the experienced shocks during the year, and agricultural information. To introduce selection bias, we assume the errors for each equation can be decomposed into an individual effect (μ_i and α_i), a time effect (ξ_t and ψ_t), an idiosyncratic effect (ϵ_{it} and ν_{it}). Each error component follows a normal distribution. The only further assumption we need is that Z_{it}' should be strictly exogenous.

[33] **In Appendix I**, we provide a robustness check estimating the relative contribution of the non-farm enterprise to household income by estimating a pooled Tobit model using as the dependent variable the share of non-farm earnings on the total household income, which is assumed to be a latent variable, observable only for positive outcomes. As before, a larger number of household members is associated with a higher share of non-agricultural income. Furthermore, the share is positively associated with non-food expenditure quartile and again the distance from the main road and market. **In Appendix II**, we provide further results on the probability for households to engage across different sectors. We restrict the sample to those households having some non-farm activity. We run six separate pooled logit regressions using as dependent variable a dummy indicating six different sectors of activity (agriculture, buying and selling, manufacturing, transport, hotel and restaurants and other). As expected, regressions results show heterogeneity amongst sectors of activity. Female household head are less likely to have a non-farm activity in the agricultural, transport and other sector, while they have a positive probability to be in the manufacturing sector. A larger number of household members is more likely to affect the starting of an activity such as a restaurant or a hotel.

Wooldridge (1995) outlines a number of estimating procedures for equation (1) where the underlying model has a FE structure. For each time period t we estimate a cross-sectional probit regression of equation (2) using Z_i as set of covariates. Then we compute for each regression the Inverse Mills Ratio (IMR)[34] that we include in the final estimation of Y_{it}^*. This procedure allows us to remove the constant heterogeneity in food consumption indicators, and agricultural technologies variables, and also to take into account the endogeneity of households to participate in the non-farm sector into the estimating equation.

For the estimation of the IMRs, the selection model includes the same set of covariates used to estimate the FE logit specification. Overall, the IMRs are statistically significant and we reject they are simultaneously equal to zero performing a Wald-test. The combined statistical significance and the rejection of the null hypothesis of these coefficients suggest that the selection model is well identified and should be no noise disturbing the output of the consequent empirical analysis. Table 3 shows results for FE models with IMRs for each cross-sectional probit estimated for 2012, 2014 and 2016 rounds[35]. We use as dependent variables the FCS (not reported because we fail to reject that *IMRs =0*), HDD score (column 1) and the total calories consumed by households during the year (column 2). For each regression performed on the mentioned dependent variables, we estimated the models restricting the sample to those households participating in the non-farm sector ($d_{it} = 1$). In this way we are estimating the relationship between food consumption indicator and the push/pull factors for household who diversify their income correcting for the probability for households to be engaged in activity outside the farm.

The coefficients maintain the same sign and similar magnitude across column one and two of table 3. On average, push factor variables such as share of adult in the household, quantity of livestock owned and precipitation positively affect nutritional status of households engaged in the non-farm sector. Again, the results confirm once again the strict relationship between non-farm sector activities and agricultural performance. The larger the household size and consequently the number of active members within the family working in non-farm activities the higher the possibility to consume a more diverse diet. On the other hand, the pull factor coefficients show mixed signs: household head age and the average educational attainment in the household negatively affect either the HDD score and total calories consumed. While, literacy level of the household head and the distance from the market are positively associated with the independent variables. Therefore, education level seems not to be necessary in order to aspire to more remunerative jobs in the non-farm sector allowing to increase the food consumption within the household. Against our expectations, the distance from the market positively affect the food consumption. A possible explanation could be that a great component of non-farm activities is still related to the agricultural sector. Such activities concentrate in the food-processing industries and some basic activities linked to clothing apparel for example. Also, the distance from the market may be related to have less competition with other activities in the urban areas.

Table 3 FE models with IMR: Food Diversity and Food Consumption Variables. Regressions performed on the sub-sample of households with some enterprise activity ($d_{it} = 1$)

VARIABLES	(1) FE- HDD Score ($d_{it} = 1$)	(2) FE- Log Tot Calories (year) ($d_{it} = 1$)
<u>*Inverse Mills Ratios*</u>		
IMR 2012	**0.660***	0.513
	[1.933]	[0.759]
IMR 2014	**1.044*****	**3.959*****
	[4.214]	[8.072]

[34] The IMR=$\frac{\phi(Z_i'\gamma)}{\Phi(Z_i'\gamma)}$, where $\phi(.)$ and $\Phi(.)$ denote the probability density and cumulative distribution functions of the standard normal distribution.

[35] We do not report results for these regression models: we use the same set of covariates used for the FE logit regression shown in table 2

IMR 2016	-0.409	-0.379
	[-1.410]	[-0.660]
Female HH Head	0.0273	**-1.121****
	[0.102]	[-2.118]
Push Factors		
Share of Adult	**0.640*****	**1.796*****
	[2.971]	[4.214]
Rain during major season right amount (=1)	0.103	**0.477*****
	[1.344]	[3.139]
Log Cultivated Area (ha)	0.0241	0.0569
	[0.768]	[0.919]
Quantity of Livestock (n)	**0.0116*****	**0.0445*****
	[4.766]	[9.273]
Pull Factors		
HH Head Age (years)	**-0.0360*****	**-0.102*****
	[-4.295]	[-6.161]
HH Head can read (=1)	**0.134***	0.122
	[1.877]	[0.867]
Avg HH Edu Year	-0.0423	**-0.184*****
	[-1.626]	[-3.561]
Log Distance Market (km)	**0.226*****	**0.910*****
	[5.098]	[10.39]
Constant	**1.388****	**15.63*****
	[2.488]	[14.16]
Observations	2,100	2,096
R-squared	0.419	0.668
Number of hh_id	1,638	1,634
Wald-Test*		
F	F(3, 450) = 9.09	F(3, 450) = 24.84
Prob>F	0.0000	0.0000

*** p<0.01, ** p<0.05, * p<0.1

*Wald-test is used in order to test restrictions $IMR_t = 0$

In Table 4 we present results for agricultural technology adoption after correcting for the probabilities of households to engage in non-farm activities for each round. We follow the same strategy implemented for studying food security. Again, we use similar set of covariates we used for nutritional status. Regarding push factors we again controlled for the household size and variables connected to the agricultural performance. Turning to pull factors we use variables to account the human capital level of the household, distance from the road and variables to proxy the level of wealth of the households. We estimated the regressions using as dependent variables the quantity of inorganic fertilizer used on the plot and the quantity of seeds. However, participating in non-farm activities does not have an impact on the quantity of inorganic fertilizers used, we also to fail to reject that *IMRs =0*, for this reason we do not the results for this specification. In column one we report results for log quantity of seeds used per hectare.

After controlling for the probability of being in the non-farm sector, having a female household head is associated with a higher quantity of seeds used. Looking at push factors, having larger households and having experienced a crop damage during the last year affect positively the quantity of seeds used. Concerning pull factors, households engaging in the non-farm sector use more seeds in the presence of a bank in the community and less the farthest they are from the main road.

Table 4 FE models with IMR: Agricultural Technology Adoption. Regressions performed on the sub-sample of households with some enterprise activity ($d_{it} = 1$)

VARIABLES	(1) FE- Log Q Used Seeds (kg) ($d_{it} = 1$)
Inverse Mills Ratios	
IMR 2012	**1.628*** **
	[2.756]
IMR 2014	**-2.186*** **
	[-2.698]
IMR 2016	0.230
	[0.416]
Female HH Head	**1.098** **
	[2.185]
Push Factors	
HH Size per AE	**0.232** **
	[2.056]
Rain during major season right amount (=1)	-0.0709
	[-0.418]
Geo Shock	**-0.773*** **
	[-3.041]
Crop Damage (=1)	**0.288* **
	[1.687]
Pull Factors	
HH Head Age (years)	0.0105
	[0.592]
HH Head can read (=1)	0.201
	[1.299]
Bank (=1)	**1.243** **
	[2.171]
Log Distance Road (km)	**-0.191** **
	[-2.359]
Log Distance Pop Center	0.0938
	[1.004]
Number of Rooms	0.0779
	[0.687]
Mobile Phone (=1)	0.175
	[0.882]
Constant	0.138
	[0.0947]
Observations	2,392
R-squared	0.090
Number of hh_id	1,898
***Wald-Test**	
F	F(3, 479) = 5.30
Prob>F	0.0013

*** p<0.01, ** p<0.05, * p<0.1

*Wald-test is used in order to test restrictions $IMR_t = 0$

Concluding, we wanted to assess using econometric tools whether the households were `pushed' or `pulled' in the non-farm sector. Descriptive statistics in the previous chapter showed that on average households are pushed to quit agriculture to compensate for experienced shocks and lower level of wellbeing. However, household can be categorized mainly in three categories depending which variables affect more their decision to engage in the non-farm sector. Using FE logit regressions, we confirm the results we obtained in the previous chapter: households tend to participate in non-farm activities because of push factors. Therefore, we can assume that households that quit agriculture remain strongly linked to it. This could be likely related to the lack of opportunities outside agriculture typical of SSA countries, lack of accumulation of human capital and other barriers to engage in this kind of activities [McCullough, 2017]. However, FE logit specification may still have some selection bias threating the reliability of our estimates. For this reason, we complement the empirical strategy with Heckman correction model using the strategy proposed by Wooldridge. In this way we can estimate the relationship between household nutritional status and input adoption for those households engaging in activities off-farm correcting for the section bias. Results also in this case confirm that push factors tend to prevail compared to pull factors variables confirming that households likely because of adverse events experienced on farm refugee in low remunerative activities off-farm.

3.4 Conclusions

In this chapter we have addressed mainly two questions: first, what is the motivation for households to participate in the rural non-farm sector, and specifically if this participation was the results of `push' or `pull' factors; and second, what is the impact of this participation on household wellbeing outcomes such as food consumption frequency, number of calories consumed and the adoption of agricultural technology.

The reduction of rural poverty in Africa in the next 50 years depends on achieving major increases in production and labor productivity. The bulk of interventions aimed at the alleviation of rural poverty alleviation focus on smallholder agricultural activity, but reductions in rural poverty may depend more on what happens off-farm than on-farm. Specifically for African countries, with strong population growth and increasingly limited agricultural resources. There is a lack of policy strategy to promote a less vulnerable non-farm sector and formalization of the off-farm economy.

The image presented by longitudinal LSMS-ISA data for Ethiopia depicts a familiar pattern for SSA countries: a large proportion of rural enterprises mainly operate for only a few months each year mainly during the dry and minor crop seasons. Female-headed households are more likely to start a non-farm enterprise because of cultural segregation by gender of agricultural activity and the social stigma associated with single women operating as independent farmers in Ethiopia. Non-farm activities represent the primary source of income for women in rural areas, but the size of these activities is smaller compared to male-owned ones. Moreover, push factors (shocks, annual precipitation, and surplus of household labor) play a greater role in determining participation in the non-farm sector compared to pull factors. Furthermore, the greatest constraints preventing the growth of non-farm enterprises are represented by access to the market, and low demand for goods. In addition, the cluster analysis confirm that the group of non-farm activities led by women represents one of the most marginalized share of households.

Results for push/pull factors are predominantly negative in relation to the possibility of non-farm employment acting as an engine of productivity growth by attracting workers off the land. Regarding the impacts of non-farm enterprise activities on household wellbeing, we found a positive effect on household food security and adoption of seeds on farm. The joint use of cluster analysis to identify and target the needs of different portion of households and econometric analysis exploiting longitudinal data may help shed light on the motivation and the impact of income diversification.

These findings finally allow us to draw some modest policy suggestions. Although the constraints faced by rural non-farm activities in Ethiopia are heterogeneous, investment in local infrastructure in rural areas will support the performance of both farm and off-farm business. Another way to add value to agricultural products is by strengthening the linkages between agriculture and non-agricultural sectors, like for instance the manufacturing sector, supporting the creation of ad hoc agro-processing industries to fill the gap of the "missing middle". The manufacturing sector is SSA and Ethiopia is mainly constituted by small food processing enterprises that mostly operate informally. Processing food industries represent a great opportunity of economic development for Ethiopia for several reasons among which to reduce the post-harvest losses and meet the demand of foods coming from urban centers. However, as suggested by econometric results the policies' effectiveness is conditional on the proper development of the country fundamentals. These fundamentals embed the adequate development of infrastructure, markets, and credit institutions. Households are not likely to increase the share of hours in modern sectors of the economy if they are confined in remote areas.

The failure of other types of industrial policies in SSA has been largely documented by the literature, since they have been normally adopted in the past without being tailored to local economic and political conditions (Mbate, 2016). As a result, most policies turned out to be ineffective as they are not context-specific and do not take into account a country's endowments of resources and initial conditions.

Finally, policies seeking to address poverty should consider the potential contribution of non-farm enterprises on household wellbeing. Without policy strategies aimed to promote business opportunities in the short run, it is difficult to hopeful that off-farm employment will generate major on-farm productivity improvements in Ethiopia.

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World Bank, 2014, ``Ethiopia Poverty Assessment'', Washington, DC. © World Bank.

-APPENDIX I

The relative contribution of the non-farm enterprise to household income: we estimate a pooled Tobit model for the share of income derived from non-farm enterprise activity:

$$S_{NF}^{*} = \alpha_0 + \alpha_1 X_{it} + \epsilon_i \; if \; \alpha_1 X_{it} + \epsilon_i > 0$$

$$S_{NF}^{*} = 0 \; if \; \alpha_1 X_{it} + \epsilon_i \leq 0$$

S_{NF}^{*} is latent variable observed for positive income share. While, X_{it} is a vector of variables including `push' (household size per adult equivalent, dependency ratio, annual precipitation) and `pull' factors (literacy of household head, number of rooms in the dwelling as proxy for wealth, and dummy for non-food expenditure quartile, having a bank in the community, distance from road, main center and market) and land holding and agricultural asset.

Table 1 Pooled Tobit Regressions: Share of Non-farm income and Share of Non-agricultural wage

VARIABLES	(1) Tobit -Rural- Sh Non-farm Inc	(5) Tobit -Rural- Sh Non-Agr Wage
Female HH Head	0.00846	-0.0261
	[0.288]	[-1.265]
Push Factors		
Dep Ratio	-0.0238	**0.0237****
	[-1.513]	[2.011]
Log HH Size per AE	**0.0866*****	-0.0151
	[2.999]	[-0.730]
Right amount rain during major season (=1)	-0.0365	**-0.0278***
	[-1.612]	[-1.733]
Log Cultivated Area (ha)	-0.00732	**-0.00857***
	[-1.075]	[-1.770]
Pull Factors		
HH Head age (years)	**-0.00348*****	-0.000680
	[-4.144]	[-1.056]
Edu HH Head (years)	0.00106	-4.55e-05
	[0.281]	[-0.0184]
Bank (=1)	0.0880	0.0490
	[0.817]	[0.602]
2nd exp quartile	**0.0894*****	-0.0265
	[2.887]	[-1.185]
3rd exp quartile	**0.111*****	**-0.0728*****
	[3.466]	[-3.175]
Top exp quartile	**0.187*****	**-0.0516****
	[5.148]	[-1.985]
Number of Rooms	-0.00928	**-0.0217****
	[-0.795]	[-2.380]
Plough (=1)	**-0.173*****	**0.0280***
	[-7.070]	[1.657]
Log Distance Road (km)	**0.0163***	-0.00312
	[1.883]	[-0.514]
Log Distance Market (km)	**0.0303****	**0.0189****
	[2.332]	[2.077]
Log Distance Pop Center (km)	**-0.0417*****	-0.0166
	[-2.967]	[-1.623]
2014	**0.283*****	**-0.0607*****
	[11.26]	[-3.463]
2016	**-0.0853****	**0.0972*****
	[-2.055]	[3.560]
Constant	**-0.238****	**0.647*****
	[-2.089]	[7.950]
Observations	6,020	1,857

*** p<0.01, ** p<0.05, * p<0.1

-APPENDIX II

Table 5 Marginal Logit Regressions: Enterprise Sectors

VARIABLES	(1) Marginal Logit - AGRI-	(2) Marginal Logit - BUYING-	(3) Marginal Logit - MANUFACT-	(4) Marginal Logit - TRANSP-	(5) Marginal Logit -HOT & REST-	(6) Marginal Logit - OTHERS-
Rural area (=1)	0.427	0.211	**-0.463****	0.0140	**-0.957****	**1.344*****
	[0.973]	[1.601]	[-1.973]	[0.0839]	[-2.497]	[3.632]
Female HH Head	**-0.430***	-0.0243	**0.277***	**-0.413*****	0.133	**-0.603***
	[-1.702]	[-0.304]	[1.752]	[-2.844]	[0.355]	[-1.871]
HH Head Age (years)	-0.00102	0.00114	0.00567	-0.000577	**-0.0175*****	-0.00376
	[-0.123]	[0.394]	[1.524]	[-0.212]	[-4.131]	[-0.604]
HH Head can read (=1)	-0.124	0.0396	-0.0351	-0.0448	-0.0536	0.00221
	[-1.343]	[0.735]	[-0.470]	[-0.491]	[-0.586]	[0.0110]
HH Size per Ae	-0.0159	-0.00100	0.00271	0.0170	**0.0619****	**-0.100*****
	[-0.706]	[-0.0534]	[0.0734]	[0.496]	[2.275]	[-3.279]
Bank (=1)	0.106	0.272	-0.410	0.0402	-0.290	-0.100
	[0.218]	[1.530]	[-1.241]	[0.259]	[-0.508]	[-0.169]
Log Distance from Road (km)	0.00269	-0.00737	0.0472	-0.0176	-0.0732	**0.0971*****
	[0.0381]	[-0.214]	[1.338]	[-0.485]	[-0.728]	[3.002]
Log Distance Populated Center	-0.0939	-0.0379	**0.0909****	-0.0376	0.159	-0.00129
	[-0.930]	[-0.741]	[2.034]	[-0.740]	[1.450]	[-0.0190]
Rain during major season right amount (=1)	-0.119	-0.126*	**0.166****	0.0636	0.382	-0.265
	[-0.956]	[-1.794]	[2.088]	[0.681]	[1.276]	[-0.698]
Food Shock (=1)	**-0.445****	0.122	0.0494	0.0812	-0.0838	0.0606
	[-2.293]	[1.163]	[0.359]	[1.003]	[-0.526]	[0.494]
Geog Shock (=1)	**0.429****	-0.133	-0.0607	0.0634	-0.150	-0.261
	[2.486]	[-1.138]	[-0.631]	[0.911]	[-0.501]	[-1.045]
Other Shock (=1)	-0.333	0.191	-0.206	-0.0422	-0.330	0.184
	[-0.880]	[0.980]	[-0.969]	[-0.172]	[-0.427]	[0.379]
Idiosyncratic Shock (=1)	-0.0311	**0.121***	-0.0843	-0.0262	-0.0486	-0.00597
	[-0.312]	[1.823]	[-0.670]	[-0.289]	[-0.204]	[-0.0484]
Price Shock (=1)	0.162	0.121	-0.0921	0.00810	**-0.488****	**-0.359***
	[1.100]	[1.317]	[-0.999]	[0.0817]	[-1.981]	[-1.848]
Crop Damage (=1)	0.203	**-0.0841***	**-0.105***	0.0282	0.122	0.0603
	[1.581]	[-1.649]	[-1.846]	[0.318]	[0.944]	[0.249]
Number of Rooms	-0.162	-0.0119	0.00980	0.0569	-0.125	**0.0860****
	[-1.514]	[-0.366]	[0.184]	[0.907]	[-1.616]	[2.296]
Cellphone (=1)	-0.0255	**0.106***	**-0.427*****	-0.0373	-0.0986	0.211
	[-0.184]	[1.846]	[-6.747]	[-0.517]	[-0.525]	[1.123]
2012	**0.814****	-0.176	-0.292	**0.464*****	**0.608***	**-1.297*****
	[2.208]	[-1.015]	[-1.315]	[2.601]	[1.652]	[-4.090]
2014	**1.369*****	**-0.360***	**0.363****	0.280	-0.274	**-0.863*****
	[3.463]	[-1.883]	[2.385]	[1.187]	[-0.512]	[-3.142]
Constant	**-2.847*****	-0.166	**-2.334*****	**-1.763*****	**-3.162*****	**-3.527*****
	[-3.563]	[-0.269]	[-3.492]	[-4.400]	[-4.437]	[-3.234]
Observations	5,204	5,204	5,204	5,204	5,204	5,204
Predict (margin at median level)	.9354***	.6120***	.8394***	.8409***	.9727***	.9525***

*** p<0.01, ** p<0.05, * p<0.1
Clustered Std Errors at woreda level
Base category not shown

CONCLUSIONS

This thesis contributes to the current literature of development economics responding two main connected research questions:

1) to what extent non-cognitive skills affect productive and allocative efficiency in rural Ethiopia;

2) what are the main drivers for Ethiopian households' income diversification into the non-farm entrepreneurship sector.

The human capital literature has expanded over the past two decades to account for all those traits concerning the sphere of emotions and personality traits which could possibly explain deviations in decision-making process. We want to contribute to the recent extension of the behavioral approach in developing countries analyzing the impact of personality traits on agricultural performance. This perspective is still largely unexplored by the recent literature. However, even though agriculture plays a crucial role in many SSA countries we are aware that the economic development does not depend uniquely on what happens on the farm but also off-farm. SSA's population is still growing rapidly (2.8%) its population is expected to double to two billion people by 2050 [UNDESA, 2015]. This underlines the compelling need to create sufficient jobs for Africa's bulging youth population. Our analysis focuses on Ethiopia which well represents the economic prospects that SSA countries are facing. To respond these two questions, we use data collected with two national representative households' surveys:

- a cross-sectional dataset for 501 rural households collected in 2012 by the University of Addis Ababa in collaboration with CEIS of the University of TorVergata and financed by FAO;
- and the LSMS-ISA longitudinal dataset which comprises 2012, 2014 and 2016 rounds.

Ethiopia's economic performance of the last two decades was characterized by strong growth. The expansion of services and the agricultural sector account for most of this growth while manufacturing performance was relatively modest. Ethiopia is among those countries that have made the greatest progress toward achieving the Millennium Development Goals but still remain one of the world's poorest countries. The government is currently implementing the second phase of its Growth and Transformation Plan (GTP II). The plan aims to continue improvements in physical infrastructure and reaching a lower-middle income status by 2025. Agriculture is the major employer and is mainly characterized by subsistence farming. However, significant progress in job creation off-farm has started to be implemented [WB Country Overview, 2017].

We report key results obtained for each research question:

1. *Emotional factors could affect decision-making, which is the role of non-cognitive skills in affecting productive and allocative efficiency in rural Ethiopia?*
    - This work represents one of the first attempt to introduce in a systematic way the non-cognitive skills' impacts on agricultural production and input adoption in a rural context in a developing country.

- Usually the other behavioral empirical applications use only constructs from one psychometric test are used, on the other hand we complement the BFI measures with the ER constructs to account for possible short-term deviations from the habitual individual behavior. In fact, an external stimuli may generate a reaction in the individual driven by the emotivity causing to `act out of character'.
- The structure of the survey allows us to use a detailed set of household and indivual characteristics to link to the personality traits measures we collect at the individual level.
- There is a contribution of non-cognitive skills in explaining agricultural productivity statistically confirmed by tests. Omitting these variables in the estimation of the production function could lead to overestimation of certain variables (input coefficients).
- Organizational skills, reliability, a strong capacity to "suppress" external emotional stimulus, and a high level of anxiety all appear to be yield-enhancing psychological characteristics. The results for the neuroticism measure merit comment. It is possible that a degree of `psychological pressure' is required to successfully perform agricultural tasks but that too much anxiety results in insecurity which depresses yields. Thi is consistent the the context of Ethiopian farming system characterized by shocks and the dependence on precipitation. On the other hand, a high degree of enthusiasm for new intellectual experiences is negatively related with yield. Intellectual curiosity may not be essential to succeed on farm activities.
- Non-cognitive skills affect input adoption decisions: higher BFI and ER scores increase the probability to use fertilizers and seeds. Holding all other variables constant at the sample mean ER measure better identify individuals most likely to adopt and disseminate new technologies. Again, higher scores in suppression trait has a positive effect on increasing input usage on farm.
- We can conclude that on average the choice to adopt fertilizers and seeds on farm is the emotional response to an external shock such unfavorable wheather conditions. For example, consider the implications of an adverse event such as a drought. First of all, this is likely to cause a decreae in the agricultural income which can affect life satisfaction in the short-term. For this reason farmers may respond to this negative event increasing the quantities of inputs used on the plot. However, on the long-term farmers with strong degree of consciousness and willingness to work for long term goals may overcome such temporary shock. This is confirmed by our results for the production function estimation, where on average BFI measures have a statistically significant impact on yield.
- Controlling for non-cognitive skills enable us to validate the Zellner et al. (1966) use of the OLS to estimate the production function within a recursive structure in which the errors on the input equations are uncorrelated with those of the production function.
- The small dimension of the sample and some descriptive statistics suggest a possible selection bias. The main consequence is that the sample is not national representative of the entire Ethiopia. Also, as stated in the literature psychometric tests performed in developing countries suffer from measurement errors the may cause a low reliability of the constructs. The measures we use are very near the threshold for good reliability, and we try to compensate analyzing in detail the relationship of these measures with other household and individual characteristics.

Viewed in this light, personality traits become a valuable analytical device for boosting agricultural productivity through inputs adoption. Non-cognitive skills can help answer why entrepreneurship appears to be limited in poor countries and help identifies what can be done to stimulate greater agricultural activity. Behavioral variables may affect both yields directly and indirectly through input use.

Policies directed towards increasing the supply of fertilizers and seeds may not lead to the expected results if non-rational perceptions of investment are not considered. Moreover, these results can be useful for discussing the literature about poverty and the approaches to the problem. Even though governments lack the prerogative to alter personality traits, however, it could encourage early childhood development interventions that aim to support the development of non-cognitive skills. Even with small interventions during the adult age can be reached great improvements in behavior patterns (such showing documentaries on successful smallholders).

To derive more conclusive policy implications could be arduous given the small sample size and the possibility of selection bias joint with the threat of measurement errors in the variables we used. However, the results we obtain can be useful to be extended to include in a more systematic way the behavioral variables into the estimation of productivity on farm in developing countries. The results we obtained -given all the limitations we face- prove the statistical validity of using such variables into the econometric analysis. A further extension of this work could include a longitudinal panel survey to track households in time. With a panel structure it could be possible to control at least for the endogeneity of the inputs in the estimation of the production function and for the time-constant household heterogeneity. Furthermore, it could be useful to submit psychometric tests in different points time. We know that non-cognitive skills -as any other skills- are not fixed in time. However, a large component is also genetically inherited. Observing whether personality traits change over time will help the debate on how much they are time variant during a life-time span. Also, should be considered the methodology proposed by Laajaj and Macours (2017) in order to control for the mismeasurements of the non-cognitive skills and improve the quality of such measures. A series of `experiments' may complement the survey collection.

2. *What are the determinants of Ethiopian households' diversification into non-farm activities? Are households pushed/pulled into these activities?*
    - Descriptive statistics show that on average households are pushed to quit agriculture to compensate for experienced shocks and lower level of wellbeing. However, household can be categorized mainly in three categories depending which variables affect more their decision to engage in the non-farm sector.
    - Non-farm push factors (shocks, annual precipitation, household size) play a greater role in determining participation in the non-farm sector.
    - Cluster analysis results are negative in relation to the possibility of non-farm employment acting as an engine of productivity growth by attracting workers off the land. In fact, a large proportion of rural enterprises mainly operate for only a few months each year mainly during the dry and minor crop seasons
    - Regarding the impacts of non-farm enterprise activities on household wellbeing, we found a positive effect on household food security and input adoption confirming that households are pushed into these activities because the neeed to overcome adverse events of farm. Therefore, we can assume that households that quit agriculture remain strongly linked to it. This could be likely related to the lack of opportunities outside agriculture typical of SSA countries, lack of accumulation of human capital and other barriers to engage in this kind of activities
    - Without policy strategies aimed to promote business opportunities in the short run (such as investments in the local infrastructure), it is difficult that off-farm employment will generate major on-farm productivity improvements in Ethiopia

These findings finally allow us to draw some modest policy suggestions. Although the constraints faced by rural non-farm activities in Ethiopia are heterogeneous, investment in local infrastructure in rural areas will support the performance of both farm and off-farm business. Second, policies seeking to address poverty should consider the potential contribution of non-farm enterprises on household wellbeing. Without policy strategies aimed to promote business opportunities in the short run, it is difficult to hopeful that off-farm employment will generate major on-farm productivity improvements in Ethiopia. Such business opportunities include the developing of the agro-prociessing food industries which represent a great opportunity of economic development for Ethiopia to fill the ``missing middle''. Even though Ethiopia experienced strong urbanization during the last years, the phenomen of the so called ``consumption cities'' observed in Ghana is tangible. This phenomenon occurs when urbanization occurred without structural transformation towards manufacturing leading to create urban centre services-based and whose demand for goods is spread toward non-food products [see Jedwab, 2012[36]]. However, it was extensively documented in the literature the failure of some industrial policies in SSA that were adopted without being tailored to local economic and political conditions. Most of

[36] Jedwab, R., and Osei, R. D. (2012). Structural Change in Ghana 1960-2010. Institute for International Economic Policy Working Paper. Washington, DC: Institute for International Economic Policy, George Washington University.

them turned out to be ineffective. In this sense, Ethiopia should careful promote business opportunities in rural areas in order to avoid prevent such failure.