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Personality Traits, Technology Adoption, and Technical Efficiency

Evidence from Smallholder Rice Farms in Ghana

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Abstract

Although a large literature highlights the impact of personality traits on key labor market outcomes, evidence of their impact on agricultural production decisions remains limited. Data from 1,200 Ghanaian rice farmers suggest that noncognitive skills (polychronicity, work centrality, and optimism) significantly affect simple adoption decisions, returns from adoption, and technical efficiency in rice production, and that the size of the estimated impacts exceeds that of traditional human capital measures. Greater focus on personality traits relative to cognitive skills may help accelerate innovation diffusion in the short term, and help farmers to respond flexibly to new opportunities and risks in the longer term.

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Personality Traits, Technology Adoption, and Technical Efficiency: Evidence from Smallholder Rice Farms in Ghana[¶]

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1. Introduction

As agriculture becomes increasingly technology-intensive, farmers' ability and willingness to adopt new technologies will be key to productivity growth and structural transformation, which will in turn determine the poverty reduction rate in settings where most of the poor still live in rural areas. The ability to adapt quickly to exogenous changes will also increase in importance as, in the context of climate change, the frequency and severity of extreme weather events is likely to increase significantly. A large literature (Feder *et al.* 1985) highlights determinants of technology adoption, including cognitive ability to accurately assess payoffs from different options, social networks that provide access to information and possibly implicit insurance (Conley and Udry 2010), the ability to bear risks or to insure against them (Suri 2011) and access to capital, especially if monetary outlays are required for adoption.

A number of recent studies highlight the important role of non-cognitive skills or personality traits as determinants of parameters, such as individuals' rate of time preference and risk attitudes that profoundly impact economic outcomes but have often been taken as given by economists.[1] In some settings, personality traits have been found to more strongly predict earnings or employment prospects than traditional cognitive skills. For example, traits such as self-discipline have been found to be more important than standard indicators such as IQ (Duckworth and Seligman 2005). They also have been found to be significant predictors of healthy behavior such as alcohol consumption and exercising (Chiteji 2010). This implies that efforts to shape personality traits early in life, when they are still malleable, can have large impacts on labor market and health outcomes (Heckman *et al.* 2010).

Conceptual models highlight that, due to spatial dispersion of activities and the need to adjust to micro-variations in climate, farming requires entrepreneurial drive, an ability to deal with complexity, and the willingness to take risks (Allen and Lueck 1998). Although they may only weakly correlate with traditional measures of human capital, skills in this area are likely to significantly affect productivity and technology adoption. Yet, though traditional human capital measures often have limited explanatory power in adoption regressions (Huffman 2001), there has been little study of personality traits' relevance to these outcomes.

As a first step towards addressing this gap, we study if and to what extent, in an irrigated outgrower scheme for smallholder rice in Ghana, personality traits affect producers' decision to adopt transplanting, their returns from adoption and their overall technical efficiency. Transplanting is a simple technology that, while requiring slightly higher levels of labor input when crops are transplanted from the nursery, has little impact on capital requirements or production risk. Yet, it can deliver significant benefits in terms of lower seed requirements, improved ability of plants to compete with weeds that reduce labor demands in the

[1] Throughout the paper we refer to 'personality traits' as comprising both personality and motivation traits.

management phase, and shorter time in the field that provides a possible basis to intensify land use by planting other crops. Although part of the technology package promoted by local extension officers, it was adopted by only a small share of producers.

The results suggest first that personality traits are indeed highly significant predictors of transplanting adoption, which in turn has a large impact on technical efficiency. Interestingly, simulations using relevant point estimates suggest the effect of personality traits on adoption is about double that of standard human capital variables. Second, beyond the channel of technology adoption, personality traits also directly enhance technical efficiency in contrast to education, the estimated effect of which is not significantly different from zero. Third, personality traits are also highly significant predictors of the returns from transplanting adoption, while human capital traits have no statistically significant relationship to returns from adoption. Disaggregation points towards polychronicity, work centrality/passion, and optimism as key variables affecting the adoption decision and efficiency of input use. In sum, non-cognitive skills that thus far have received limited attention from agricultural economists affect producers' technical efficiency as well as their adoption decisions and adoption outcomes.

The findings imply that further study of the effects of personality traits on agricultural sector outcomes is warranted to better understand whether these traits are also relevant for more complex technologies or risky adoption decisions than those studied here. From a policy perspective, they suggest that early childhood development interventions targeting non-cognitive skills may have high returns in rural, low-income country contexts. Personality traits may also help identify individuals most likely to adopt certain technologies or to benefit from such adoption.

The paper is organized as follows: Section 2 discusses determinants of agricultural technology adoption and the effects of personality traits on economic outcomes. Section 3 provides details on the definition and measurement of personality traits, summary statistics on agricultural production in the sample and the econometric approach. Section 4 presents results with respect to technology adoption and technical efficiency. Section 5 concludes with policy implications and suggestions for further research.

2. Background and justification

To motivate our study, we review the literature on determinants of agricultural technology adoption, noting the absence of a discussion of personality traits as potential determinants of adoption decisions. A brief review of recent literature finding that many 'fundamental' economic parameters are potentially affected by personality traits suggests that, directly or indirectly, such traits may affect adoption decisions and that measurement of such traits to explore this relationship will be of interest.

2.1 Factors underpinning agricultural technology adoption

Improved technology is critical for economic growth and assumes even higher importance in smallholder settings where new technologies can enhance yields, reduce risk, and contribute to better outcomes in a range of other ways. Obstacles to smallholder technology adoption traditionally identified in the literature include human capital, credit, wealth, information and transport constraints, risk aversion, poor tenure security, lack of economies of scale and lack of complementary inputs (Feder *et al.* 1985). Recent literature has focused on models of learning and risk aversion in the presence of credit and insurance market failures (Foster and Rosenzweig 2010) that highlight the importance of prior adoption decisions and outcomes of farmers within an agent's network.

Cognitive skills are essential to quickly acquiring and processing information not only on the availability of new technologies but also on how to apply them in a given setting. It is thus not surprising that education, as the most commonly available proxy for such skills, emerged as a key determinant of adoption decisions. Skinner and Staiger (2005) show that education and measures of individuals' social network were the only predictors of adoption significant for all of four key technologies adopted by US farmers over the 20th century. Recent literature found that education improves learning (information processing), and increases the adoption of new technologies and the efficiency of their application (Foster and Rosenzweig 2010).

But education itself may be endogenous if it is particularly sought in settings where returns to such skills are high. Indeed, Foster and Rosenzweig (1996) use Indian panel data to show that returns to education are higher in areas where agricultural technologies are available for adoption and that demand for education increased where, due to availability of new agricultural technology, returns to education had increased (an effect limited to land-owning households). This is consistent with the finding of many studies that, beyond basic numeracy, education is a statistically insignificant determinant of adoption decisions (Huffman 2001). For example high levels of unobserved heterogeneity are found for GM seed adoption in the US (Barham *et al.* 2015) and it would be of interest to explore if this variation could be explained by personality or non-cognitive traits.

One non-traditional factor recently highlighted as important to smallholder adoption decisions is social learning (Conley and Udry 2010). Farmers observe the effect of adopting a new technology on individuals in their network and then update their beliefs and decisions in response. At least in the long term, learning from neighbors seems to be more important to promoting the adoption of fertilizer and improved seeds than learning from extension agents (Krishnan and Patnam 2014) suggesting that different information sources are weighted differently by farmers. For instance, networks which individuals choose to join have been found to be more effective at facilitating technology adoption than those based on mere proximity (Liverpool-Tasie and Winter-Nelson 2012).

2.2 Can personality traits explain adoption and agricultural productivity?

The ability to solve abstract problems, commonly referred to as cognitive skills, is distinct from motivational and personality traits, generally referred to as non-cognitive skills (Borghans *et al.* 2008). The psychology literature defines the latter as "relatively enduring patterns of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances" (Roberts 2009), a definition used in recent literature, such as Almlund *et al.* (2011), aiming to bridge personality psychology and economics. In practice, the correlation between indicators of non-cognitive and cognitive skills is often very low, partly because non-cognitive skills rely on a much wider array of functions (Brunello and Schlotter 2011).

Although the precise definition and measurement of non-cognitive skills varies across studies, there is broad support for a high order taxonomy of personality traits referred to as the five factor model (Borghans *et al.* 2008). The five factors are (i) agreeableness or willingness to help other people; (ii) conscientiousness, i.e., a preference for following rules and schedules and high levels of organization and dependability; (iii) emotional stability or being relaxed and independent; (iv) openness to experience including autonomy, initiative and internal locus of control; and (v) extroversion, i.e. gregariousness and preference for human contact. While some use the conjoint of these as non-cognitive skill indicators, others argue that informed selections of lower order traits (referred to as "facets") may be better predictors of domain-specific outcomes (Paunonen and Ashton 2001; and Roberts *et al.* 2005).

A surge of recent research has found non-cognitive skills and personality traits to be powerful predictors of schooling and labor market success with a predictive ability equal or superior to that of cognitive skills (Blanden *et al.* 2007; Heckman and Rubinstein 2001; Heckman *et al.* 2006; Heineck and Anger 2010). For example, a longitudinal study for the US shows that moving an individual from the 25^{th} to the 75^{th} percentile of non-cognitive ability at age 14 to 21 increases males' and females' wages by 10 and 30 points and their probability of employment by 15 and 40 points, respectively (Heckman *et al.* 2006). General Educational Development (GED) graduates have cognitive ability equal to that of high-school graduates, but are less successful than their peers due to lower non-cognitive skills (Heckman and Rubinstein 2001). The Perry preschool program, an experimental intervention given to individuals with equal IQ early in life, had far-reaching impact on a wide range of outcomes (Heckman *et al.* 2010) by affecting participants' motivation and personality. For a sample of American middle school students, self-discipline was found to matter more than twice as much as IQ for final grades (Duckworth and Seligman 2005). Studies find non-cognitive skills to predict risk taking, violence, illegal activities, smoking and drinking (Carneiro *et al.* 2007; Chiteji 2010; Heckman *et al.* 2006).

The importance of non-cognitive skills emerging from such studies has led some to argue that the role of cognitive skills in shaping socioeconomic outcomes (Jensen 1998) may have been overstated and that such over-emphasis on cognitive skill to the exclusion of other factors can bias evaluation of interventions and public or private investments to promote human capital (Heckman 2000).[2] Yet, for many sectors, evidence on the impact of non-cognitive skills on economic outcomes in low-income contexts is only beginning to emerge. For example, studies argue that non-cognitive skills predict the probability of business innovation for micro-entrepreneurs (De Mel *et al.* 2009) and default for micro-loan applicants (Klinger *et al.* 2013).

Exploring the impacts of personality traits on adoption of agricultural technology in Sub-Saharan Africa is germane for two reasons. First, agriculture provides the main income source for the vast majority of Sub-Saharan Africans and is therefore fundamentally important to poverty reduction, but the continent is far from the agricultural technology frontier and most increases in agricultural production have so far been due to expansion along the extensive rather than intensive margin. Second, many studies find traditional measures of human capital to have little impact on production efficiency or adoption of beneficial innovations (Huffman 2001), suggesting that other factors may be key determinants of these outcomes. Moreover, some factors identified in recent literature as strong predictors of adoption decisions–e.g. the size of an individual's network or his/her risk preferences–may arguably be affected by personality traits.

3. Data and descriptive statistics

This section uses survey data to characterize the study setting, which is dynamic and well integrated with peri-urban labor markets, and to highlight differences among sample farmers. We explain how key dimensions of personality traits are measured and how they differ among individuals in our sample before discussing in detail the channels through which they might affect technology adoption and technical efficiency.

3.1 Study setting, data sources, and key household characteristics

We use data from the Kpong and Weta irrigation schemes, located in Ghana's Eastern and Volta Regions. Cultivators of rice plots were selected randomly from a listing of all cultivators in the schemes during the 2013 major season. With the sample stratified by gender and scheme,[3] data were collected on agricultural production, household income, livestock and other assets, credit, decision making, and expenditures in the 2012 major season (April-September). After dropping non-useable data,[4] we have 1,194 cultivators with 1,778 rice parcels.

[2] An analogy may be the shift from a focus on school enrollment to a focus on improving school quality (e.g. Hanushek and Woessmann 2008).
[3] All female farmers were included to allow sufficient statistical power for analysis by gender sub-group.
[4] Of the 1,600 farmers in the sample, 159 were dropped because they did not cultivate irrigated rice parcels, 80 because accurate harvest information was not available, and another 184 due to missing control variables.

Household-level descriptive evidence for the entire sample, for the two schemes, and for those who transplant and those who broadcast is reported in table 1.[5] One-third of the sampled cultivators are female, 48% of whom are also head of their own household. The share of cultivators who can read and write is 12 percentage points higher in Kpong than in Weta (58%), compared to 79% among men; literacy among women is 40%. Mean cultivator age is 46 with a mean of 9 years of education completed, a value that is 3.5 lower for women (9.9 years vs 6.2). Most sampled farmers' primary occupation is agriculture (89%). Still, the diversified nature of the environment is illustrated by the fact that 53% have access to non-farm enterprise income, and 31% to wage income. The mean value of household assets is GHC 4,556 and that of livestock GHC 428. With GHC 6,880 vs GHC 3,674, asset endowments were significantly higher in Weta than in Kpong.

Table 2 provides evidence at the field level, pointing towards substantial variation in terms of application of agricultural techniques, chemical inputs and harvest mechanization. While the average size of irrigated parcels is similar between Kpong and Weta (0.85 vs. 0.75 ha), yields are higher in Kpong (5 t/ha) than in Weta (3.1 t/ha), with farmers in the former also obtaining somewhat higher monetary returns due to slightly higher quality. For 74% of parcels, the cultivator has the use rights, having acquired them on average 24 years ago.

Land use rights are allocated by the government and non-transferable except through inheritance, and indeed 74% of parcels (71% in Kpong and 84% in Weta) are cultivated by their owner. Informal leasing of about 26% of sample parcels is thus in contravention of official regulations. Most of these transfers were for the long term and the share of informal leasing is, with 15%, much lower in Weta than in Kpong (30%), possibly due to a more active non-agricultural labor market there. Also, leasing does not seem a deterrent to the use of transplanting, with 30% of transplanted parcels being leased.

Use of herbicides and insecticides is common in both schemes, while fungicide application is more common in Kpong (81%) than in Weta (29%). On the intensive margin, the value of herbicide per hectare in Weta is 26% higher, while the value of insecticide and fungicide per hectare is 76% and 80% lower, respectively. Inorganic fertilizer use in various formulations is widespread, though less than 5% use organic fertilizer. Applying formulas to compute pure nutrients points towards little difference in N application but slightly lower levels of P in Weta.[6] Also, with 3% of producers practicing it, transplanting is less common in Weta than in Kpong (49%).

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[5] Transplanting is less widespread in the Weta than in the Kpong irrigation scheme (3% vs 49%). Tables 1, 2 and 3 therefore compare farmers who transplant with those who do not within Kpong only in columns 4 and 5 to avoid conflating differences between transplanters and non-transplanters with differences between Weta and Kpong.

[6] Cultivators located in Weta apply 30% less NPK-Activia per hectare than those in Kpong, but offset this with higher use of Urea and Ammonia, resulting in comparable levels of N application. There is no statistically significant difference in application of nutrients between male and female cultivators.

Transplanting whereby, rather than seed being broadcast, seedlings are grown in a nursery and planted on the field later has a number of advantages. Total time required in the field is shorter, potentially allowing more intensive use of a given piece of land. Less seed is needed as germination rates in the nursery are higher. Seedlings are more developed at the time of planting and thus better able to compete with weeds. While labor needs at the transplanting stage are higher, this may be somewhat offset by lower requirements for weeding and other management later on.

In Kpong, yields of farmers who transplant are significantly higher than those who fail to do so in the same scheme with a yield difference of 12% (or 0.56 t/ha) in Kpong. Columns 4 and 5 show that transplanting farmers tend to be slightly younger (by 1.6 years) and more educated (by 0.7 years) than non-transplanters, spend 42% less on seed per hectare (262 GHC vs 151 GHC), use 36% more labor on land preparation (25.3 vs 18.6 days/ha) but, presumably due to higher yields, use similar levels of labor for field management and harvest. Male and female cultivators are equally likely to use transplanting to establish their crop.

Mechanized ploughing is almost universal, although the technology differs–power tillers are prevalent in Kpong and tractors in Weta, where the amount spent on ploughing per hectare is 43% lower. About half of farmers harvest using a combine, while the other half cut and thresh their crop manually, a practice that is more common in Weta (59% vs 48%). Overall, cultivators report 119 days between completion of planting and completion of harvest. Despite lower yields, the number of labor days spent is about 30% higher in Weta than in Kpong, with a higher share of days allocated to crop management. Female farmers perform a greater portion of the work in Weta, with roughly double the number of female family and hired labor days per hectare. Perhaps because they broadcast seed rather than transplant, Weta farmers spend 25% fewer days on planting but more days on management. In both locations, most harvest labor is hired.

3.2 Measuring personality traits

To measure levels of cultivators' non-cognitive skills, we use responses to 25 questions developed by industrial psychologists and group them into 9 categories. The questions, reproduced in appendix A together with the relevant groupings, are identical to those in De Mel *et al.* (2010).[7] Questions were translated into the local languages (GA-Dangme and Ewe) with responses coded on a scale of one to five, five indicating "agree strongly" and one indicating "disagree strongly". After rescaling responses from -2 to 2, responses in each of the 8 categories are summed up and divided by the number of responses per category to obtain an indicator in the [-2,2] range.

[7] They have been shown to predict innovation and success for micro entrepreneurs in Sri Lanka (De Mel *et al.* 2009). Having the same set of questions allows us to test if traits that predicted micro-entrepreneurial success in Sri Lanka are relevant for smallholder productivity and technology adoption in Ghana, implying some transferability of personality traits across activities and cultural contexts. The procedure is identical to that in De Mel *et al.* (2010), except that the construct values there are not divided by the number of questions comprising the category.

The first four traits can be conceptualized as aspects of personal motivation. Achievement orientation and power motivation are defined in McClelland's theory of motivational needs (McClelland 1985). The former is a desire to set and achieve difficult but obtainable goals and to receive performance related feedback, while power motivation is a desire to control or influence others. Tenacity is the tendency to persist in pursuit of tasks in the face of obstacles (Baum and Locke 2004; Gartner *et al.* 1991). Given their similarities, we combine work centrality and passion into a single construct where work centrality is a belief about the degree of importance work plays in life (Misra *et al.* 1990) and work passion is a measure of love or passion for one's work (Locke 2000). Personal beliefs are captured by variables reflecting internal locus of control and optimism. Internal locus of control is an individual's belief about the degree to which she can control events that affect her (Rotter 1966). Optimism is a belief that uncertain events will tend to work out well.

Traits related to how individuals approach work tasks are polychronicity, organization and impulsiveness. Polychronicity is defined as "The extent to which people in a culture prefer to be engaged in two or more tasks or events simultaneously; and believe their preference is the best way to do things." (Bluedorn *et al.* 1999). Organization is the extent to which an individual approaches tasks in a systematic way and is a lower level facet of the big five factor conscientiousness. Impulsiveness is a tendency to respond to internal or external stimuli rapidly without thought of the consequences (Barratt 1959; Patton *et al.* 1995). Frederick *et al.* (2002) argue that, along with compulsivity and inhibition, impulsiveness is one of 3 sub-dimensions of the time preference parameter commonly estimated by economists.

In addition to the above, we include digitspan as an objective measure of cognitive skill, in particular numeracy and short-term processing ability. This measure is obtained by reading respondents two sets of numbers with 3, 4, 5, 6 and 7 digits, and asking them to repeat the longest number they could remember. It is then defined as the highest number of digits at which at least one of the sets was repeated correctly. Table 3 compares the mean value of the personality indicators and digitspan between cultivators in Weta and Kpong and also between broadcasters and transplanters in Kpong. It points towards significant differences between the two irrigation schemes, possibly related to environmental factors or culture.[8] Columns 4 and 5 compare the mean value of the indicators between those who transplant and broadcast in Kpong, suggesting that at a descriptive level adopters have higher levels of optimism and weakly significant higher levels of digitspan and internal locus.

[8] While the literature suggests that the factor analysis deriving the Big Five Factor structure can be replicated across cultures (McCrae and Costa 1997), personality indicators for individuals may vary systematically across areas due to environmental or cultural characteristics (see McCrae, Terraciano et al. 2005).

3.3 Exploring impacts of personality traits on technology adoption

To assess factors that may contribute to adoption of transplanting or mechanized harvesting, we use a logit model. Predictors include characteristics of cultivators (age, education, gender), their household (physical assets and livestock), parcels (area cultivated, soil quality and slope, existence of erosion control/water harvesting facilities), and the full set of cognitive and non-cognitive indicators specified above.

Adoption theories have postulated four main determinants of technology adoption decisions, namely (i) perceived equilibrium increase in efficiency or performance expectancy (PE); (ii) the perceived economic ease of adoption or effort expectancy (EE);[9] (iii) the perceived *social benefits*, including status and influence (SI); and (iv) the perception of facilitating conditions including future availability of infrastructure or services to support the technology (Venkatesh *et al.* 2003). These determinants depend on the actual characteristics of the technology, the context and the human capital of potential adopters (including personality traits), but also on potential adopters' perception of these characteristics, which may in turn be influenced by personality.

We expect optimism to positively associate with perceptions related to all four determinants and in turn adoption. High levels of polychronicity and organization are likely to improve effort expectancy and, for suitable technologies, performance expectancy. Power motivation and achievement motivation may operate through the channels of effort expectancy and greater responsiveness to social influence. The latter effect would depend on whether adoption is expected to increase social authority or perceived achievement. Likewise, we expect locus of control, and work centrality and passion to ease effort expectancy and thereby increase adoption. We have no clear prior on the relationship between impulsiveness and adoption, since impulsiveness may increase intent to adopt but reduce successful completion of adoption.

As a direct measure of cognitive ability that may to some extent overcome measurement bias resulting from the standard use of years of formal education as an imperfect proxy, we expect digitspan to be associated with higher levels of technical efficiency. This is supported by the literature that has shown cognitive ability to be strongly correlated with better labor market outcomes (Jensen 1998). Since digitspan measures individuals' ability to process new information and learning, which has been shown to be essential for adoption of complex technologies (Foster and Rosenzweig 2010), we also expect it to positively affect technology adoption.

3.4 Do personality traits affect technical efficiency?

While personality traits may affect technology adoption, they are also likely to affect technical efficiency directly. To determine whether there is an independent effect, we use a stochastic production frontier model

[9] This could also be understood as a reversed scale of the perceived cost of adoption.

first proposed by Aigner *et al.* (1977) and Meeusen and Van den Broeck (1977) to analyze the determinants of inefficiency within the sample. We use a slight variation on these procedures by Huang and Liu (1994) that applies maximum likelihood to estimate the stochastic production frontier and sources of inefficiency in one step. The inefficiency term is specified as $\mu = \delta_i Z_i + \varepsilon$, where ε is a normally distributed error term with mean $\delta_i Z_i$ that is truncated from below at -$\delta_i Z_i$ (so that μ is strictly positive), and Z_i is a vector of potential sources of inefficiency. This allows mean technical efficiency to be conditional on managerial characteristics. Assuming a flexible translog production function, the model takes the form:

$$\ln(Y) = \sum_i \beta_i \ln(X_i) + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln(X_i)\ln(X_j) + \theta_k G_k - \mu + v \quad (1)$$

where Y is yield per hectare; X_i are physical inputs including the area of land planted, the amount of labor, nitrogen and phosphate applied per hectare, and the cost of crop protection chemicals (herbicide, insecticide and fungicide), mechanized ploughing and mechanized harvesting applied per hectare; G_k are parcel characteristics including dummy variables for subjective soil quality, whether the parcel was fallow during the past 5 years, and whether use rights were obtained directly from the government or from another individual who was allocated these rights; and v is a normally distributed error term with mean 0. Technical inefficiency μ is defined as above by $\mu = \delta_i Z_i + \varepsilon$ where Z_i denotes farmer attributes (age, education, gender, household size, personality traits) and technology including dummy variables for irrigation scheme, whether transplant or broadcast seeding is used, and seed type. ε is normally distributed with mean zero, but truncated from below at $-\delta_i Z_i$.[10]

In addition to the conventional factors included in regressions of this type (Liu and Myers 2009; Sherlund *et al.* 2002), previous research has linked motivational traits (Dunifon and Duncan 1998), locus of control (Groves 2005; Heckman *et al.* 2006), and organization with labor market outcomes, leading us to expect a positive association with technical efficiency. The time management skills measured by polychronicity may affect smallholders' technical efficiency and ability to synchronize multiple income streams.[11] Higher discount rates in early life, due to impulsiveness, have been shown to negatively impact later life success (Castillo *et al.* 2011), and we expect this to negatively correlate with technical efficiency.

4. Estimation results

Personality traits, especially polychronicity and optimism, are estimated to be more statistically significant and quantitatively important contributors to the adoption of transplanting—in turn a major predictor of

[10] The maximum likelihood estimation is performed in STATA 13 using the sfcross command (Belotti *et al.* 2012). Likelihood ratio tests are used to test for significance of the Z terms.
[11] Psychology literature on farmers' stress consistently shows time management to be a leading factor (McGregor *et al.* 1995; Walker and Walker 1987; Deary et al. 1997; Pollock et al. 2002; Alpass et al. 2004).

technical efficiency—than traditional human capital indicators, with an estimated impact about double that of education. In addition to this indirect effect, polychronicity, work centrality and digitspan also increase technical efficiency directly. In our setting, personality traits are thus arguably more important predictors of cultivators' technology adoption and levels of efficiency than those traditionally used in the literature.

4.1 Determinants of technology adoption

While inclusion of all 9 personality traits discussed above allows us to test for their joint significance, testing for significance of individual factors requires us to account for potential collinearity between them. To do so, we first check for collinearity by calculating each predictor's variance inflation factor (VIF).[12] As the highest VIF for the conditional mean term is below 2, we conclude that collinearity is very low. As an additional check, we then use 4 model selection techniques to limit the specification to the most important non-cognitive predictors and check if their statistical significance changes as a result. We use three techniques to do so, namely (i) restricting the model to characteristics we expect to be most important based on the literature; (ii) allowing statistical techniques, specifically forward stepwise regression[13] and least angle regression (Efron *et al.* 2004)[14] to select predictors; and (iii) introducing each trait individually while removing all others from the model.

Marginal effects from logit estimation of efficiency determinants are reported in table 4 with columns for inclusion of all traits (col. 1); selection of traits based on the literature (col. 2); LARS and stepwise selection methods as described above (cols. 3 and 4). Coefficient estimates for specific variables change little across specifications. Consistent with the literature, higher levels of physical assets and education are positively associated with adoption. For adoption of transplanting, the psychometric variables are jointly significant at the 5% level for the first 3 models, and at the 1% level for the stepwise model.

The three most significant traits are polychronicity, optimism, and work centrality/passion (though the latter reduces the likelihood of adopting transplanting). Polychronicity is significant at 1% in all specifications. Optimism is significant at 10% or 5%, except when introduced independently, where it is insignificant.

[12] VIF is a measure of how much the variance of the predictor's coefficient is increased by the inclusion of other predictors in the model. Hair *et al.* (1995) suggest that a VIF below 10 indicates inconsequential collinearity.

[13] Forward stepwise regression is a standard model selection algorithm that, starting with no variables in the model, sequentially adds the predictor most correlated with the residual of the outcome variable after all variables currently in the model are controlled for until no predictor outside of the model meets a minimum p-value when added to the model (in this case, 0.09). Predictors inside the model that no longer meet a minimum p-value requirement (in this case 0.1) as a result of the addition of other variables to the model are then removed until all predictors in the model meet the minimum significance requirement. The process is then repeated until all predictors inside and outside the model are above or below their minimum significance requirement, respectively. For the stochastic frontier selection inclusion of all production function variables is forced, while the algorithm selects-in covariates from the conditional mean.

[14] Least angle regression (LARS) is similar to a forward stepwise procedure but avoids arbitrarily removing predictors highly correlated with the outcome variable that happen to be correlated with another predictor selected earlier. It does so by increasing the coefficients on covariates currently in the model in their joint least squares direction until a variable not currently in the model has as high a correlation with the residual as the variables currently in the model. At this point, that variable is added and the procedure is repeated. LARs achieves the same result as the LASSO selection technique (Tibshirani 1996) except when the coefficient of a variable already in the model hits zero, in which case it is removed and the joint direction is recomputed (Efron *et al.* 2004).

Work Centrality/Passion is negatively associated with adoption of transplanting, possibly because of a more traditionalist attitude. This relationship is significant at 5% or 1%, except when introduced independently, where it is insignificant. For the adoption of mechanized harvesting, psychometric characteristics are jointly insignificant, regardless of the specification and none of the individual constructs or standard human capital indicators are individually significant either.[15]

To compare the estimated impacts of personality traits with those of standard measures of human capital indicators, figure 1 plots the predicted probability of transplanting adoption at each decile of the distribution of education, age and experience (panel A), the non-cognitive traits (panel B), and the digitspan as an objective measure of numeracy and processing capacity (panel C) holding all other covariates constant at the sample mean.[16] The 95% confidence band implied by standard errors calculated using the delta method is also indicated.

Panel A suggests concave predicted impacts of higher levels of human capital on adoption of transplanting, i.e. increases in education will be most significant at lower parts of the distribution, in line with the notion that a minimum level of literacy or numeracy is needed for awareness and understanding of the potential benefits from new technology.[17] At the same time, predicted impacts decrease rapidly when moving up the distribution,[18] with marginal gains from higher levels of education negligible beyond the 3rd or 4th decile. Better measurement of actual cognitive ability does not change this picture; in fact plotting predicted levels of technology adoption against the digitspan as a more precise measure of cognitive ability in panel C points towards a flat relationship. The predicted overall increase in the probability of adoption due to a hypothetical move from the 1st to the 9th decile of the distribution of traditional human capital indicators is 15 percentage points.

A display of the same relationship for non-cognitive skills in panel B points towards interesting differences. The relationship is estimated to be convex rather than concave, i.e. the marginal effect of increments in non-cognitive skills increases as one moves up the distribution. Also, with 34 percentage points, the predicted increase in the probability of adopting transplanting associated with moving from the 1st to the 9th decile of the distribution of non-cognitive skills is more than double that of standard human capital. This implies that simple non-cognitive skill indicators can identify individuals most likely to adopt and disseminate technologies similar to transplanting, potentially speeding the diffusion process. To the extent

[15] Results for mechanized harvest adoption are available from the authors on request.

[16] To allow consistent interpretation, values for traits with negative coefficients are re-scaled so that higher deciles increase the probability of adoption. In particular, the indicators for cultivator achievement motivation, power motivation, work centrality/passion and age are reversed.

[17] The three panels of figure 1 display the predicted probability of adopting transplanting at each decile of the distribution of (i) education, age and experience as traditional human capital variables (panel A); (ii) all non-cognitive traits included in table 5 (panel B); and (iii) the digitspan as a possibly more accurate measure of cognitive ability (panel C). All other covariates are held constant at their sample means and the 95% confidence band is computed using the delta method.

[18] The increase in predicted probability of adoption is driven almost entirely by education, rather than age or experience.

that a similar relationship holds for adoption of more complex technologies, the results suggest that investment in early childhood development of non-cognitive skills may substantially affect the adoption of agricultural technology over the long run.

4.2 Determinants of technical efficiency

We estimate a stochastic production frontier to explore if, beyond affecting adoption of transplanting, non-cognitive skills affect productive efficiency more generally. Elasticities and inefficiency parameters from a translog specification are reported in table 5.[19] Column 1 reports results from the model without personality traits, while columns 2 through 5 report results after including all personality traits, a pre-selection of traits, and LARS and stepwise selections as defined for table 4. Estimated coefficients for conventional inputs are positive and highly significant throughout with the exception of the number of labor days, which may point towards application of labor in fixed proportion to purchased inputs. Lower levels of self-reported soil quality are estimated to reduce output (by 8% and 41% for fair and poor compared to high quality). Parcels that had been left fallow have significantly lower yields, suggesting a limited role of fallowing in restoring fertility in an environment where use of fertilizer and other chemicals is widespread.

The continuation of table 5 on the following page reports the inefficiency parameters, including the impact of personality traits. A number of interesting results emerge: First, standard human capital indicators are individually and jointly insignificant throughout, even after removing variables with which they might be collinear via model selection. Second, transplanting is estimated to increase technical efficiency, an effect that is significant at 1% in all specifications. Likewise, household size is estimated to be a significant determinant of efficiency regardless of specification, suggesting labor market imperfections. Finally, personality traits are jointly significant at 5% when including all traits and 1% for the LARS and stepwise selected models, suggesting that, beyond impacting efficiency indirectly via adoption decisions, personality traits also have a direct efficiency-enhancing effect. A look at the dimensions of these traits shows that polychronicity and work centrality/passion are significant at 1% and 5%, respectively, in all specifications. Digitspan is insignificant except for in the stepwise selected model and when introduced without non-cognitive traits (not shown), where it is significant at the 10% level. The point estimate for digitspan is about one-third that of polychronicity or work centrality. None of the other indicators is significant.

Predicted impacts on technical efficiency due to hypothetical moves from the 1st to the 9th decile in the distribution of traditional human capital (education, age, experience) and non-cognitive skills, respectively, illustrate the associated magnitudes. For traditional human capital, such a move is predicted to increase technical efficiency from 66.4% to 67%. Based on our production function, this would translate to a 0.9%

[19] The Cobb-Douglas is rejected in favor of the translog at the 1% level for specifications both with and without non-cognitive traits.

increase in output, an income gain of GHC 39 (USD 20 using the June 2012 exchange rate) per hectare and season. By comparison, an equivalent move in the distribution of personality traits is predicted to increase technical efficiency from 64.5% to 68.5%, equivalent to a 6.2% output increase or an income gain of GHC 268 (USD 139) per hectare and season. With two irrigated seasons per year and a 12% discount rate, the net present value of the associated income increases is equivalent to USD 337 and USD 2,314 per hectare, respectively.

The Huang and Liu (1994) non-neutrality model also allows for technical inefficiency related to managerial characteristics to vary by the level of inputs applied, if interactions between inputs in the production function and sources of inefficiency are included in the Z vector of equation (1) above. Although the number of parameters in the production function and inefficiency term are too high to allow estimation of the complete non-neutrality model, we are able to interact the inefficiency parameters with the transplant adoption indicator as a robustness check. Table 6 reports estimated marginal effects at the mean and coefficients of the interaction terms for this specification.

The main results are robust to this specification: The standard human capital indicators are individually and jointly insignificant, while personality traits are significant at the 1% level and polychronicity, work centrality and digitspan remain individually significant. Achievement orientation and power motivation are now individually significant as well. The interaction terms from this specification imply that personality traits are also more predictive of the benefits of adopting the transplanting technique, suggesting that personality indicators may be useful for predicting which individuals will benefit most (and least) from adoption. Standard human capital trait interaction terms are jointly and individually insignificant. Farmers with high levels of achievement orientation and power motivation appear to benefit more from transplant adoption, while those with larger households benefit less (all 3 effects are significant at the 5% level).

5. Conclusion

Our paper contributes to the literature by showing that, in the Ghanaian irrigated rice schemes studied here, non-cognitive skills that thus far did not receive strong attention in the agricultural economics literature affect producers' adoption decisions, technical efficiency, and adoption outcomes. Simulations suggest that the effect of personality traits on adoption is about double that of standard human capital variables. Beyond their impact on adoption decisions, these factors also affect smallholders' technical efficiency directly. Disaggregation points towards polychronicity, work centrality/passion, and optimism as key variables affecting the adoption decision and efficiency of input use.

While this suggests that accounting for personality traits in efforts to promote new technologies may be warranted, further study of the effects of such traits on agricultural productivity should help to understand whether these traits are also relevant for more complex technologies or more risky adoption decisions than those studied here and the precise mechanisms at play. To the extent that such study supports our findings and we are able to interpret them as causal effects, early childhood development interventions that aim to support development of non-cognitive skills may be warranted not only in urban but also in rural contexts.

Table 1: Farmer-Level Characteristics

	Total	Irrigation Scheme			Crop Establishment Mode (Kpong only)		
		Kpong	Weta		Broadcast	Transplant	
Household & main cultivator characteristics							
Female headed household (%)	18	18	17		16	20	*
Female cultivator (%)	33	33	34		32	33	
Age (years)	45.4	44.0	49.0	***	44.8	43.2	**
Education (years)	8.7	9.3	7.1	***	9.0	9.7	**
Can Read and Write (%)	67	70	58	***	65	75	***
Farming Main Occupation (%)	89	89	89		90	88	
No. HH Members	5.9	5.7	6.2	***	5.8	5.9	
Household assets and land							
Physical (non-land) assets (GHC)	4556	3674	6680	***	3022	4329	***
Livestock (GHC)	427.5	415.2	457.6		474.7	356.1	
No. of parcels	3.08	2.69	4.03	***	2.63	2.74	
No. of irrigated parcels	1.59	1.72	1.29	***	1.54	1.89	***
HH Ag. land irrigated w rice (%)	70	83	38	***	80	86	***
Income in 2012 major season							
Cultivator had any wage inc. (%)	19	20	16		20	20	
Anyone in HH had any wage inc. (%)	31	33	28		33	33	
Household wage income (GHC)	268	304	181		265	342	
Received non-farm enterprise income (%)	53	49	61	***	48	51	
HH non-farm enterprise inc. (GHC)	930	864	1091		701	1026	
Total income from agricultural parcels	3015	3847	975	***	3124	4566	***
Net remittances and other inc. (GHC)	-48	-64	-9	*	-58	-69	
Total net household income (GHC)	4166	4952	2239	***	4032	5865	***

Source: Own computation from World Bank Kpong and Weta irrigation scheme survey.
Asterisks denote significance of t-tests for equality of means between the preceding columns: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: Parcel Level Characteristics

	Total	Irrigation Scheme			Crop Establishment Mode (Kpong only)		
		Kpong	Weta		Broadcast	Transplant	
Harvest per hectare (Kg)	4572	5033	3143	***	4756	5315	***
Value of yield per hectare (GHC)	4486	5033	2794	***	4756	5315	***
Plot characteristics & yield							
Planted area (Ha)	0.83	0.86	0.73	***	0.80	0.91	***
Parcel owned	74	71	84	***	71	70	
Parcel rented-in	26	29	16	***	29	30	
Non-Labor inputs							
Value of seed applied/Ha (GHC)	194	207	152	*	262	151	***
Any herbicide used	100	100	99	***	100	100	
Any insecticide used	91	98	72	***	98	98	
Any fungicide used	68	80	29	***	79	82	
Nitrogen/ha (kg)	151	150	154		150	150	
Phosphate/ha (kg)	58	62	43	***	61	63	
Transplanting used	38	49	3	***	0	100	
Labor inputs							
Male family labor\ha (days)	24.8	24.2	26.4		25.2	23.3	
Female family labor\ha (days)	17.8	14.5	27.9	***	15.1	14.0	
Male child family labor\ha (days)	6.4	5.1	10.3	***	6.2	4.0	*
Fem. Child family labor\ha (days)	3.9	3.3	5.6	**	4.3	2.3	**
Male hired labor\ha (days)	30.5	34.0	19.6	***	28.9	39.3	***
Female hired labor\ha (days)	25.3	19.7	42.6	***	16.7	22.8	***
Land preparation labor (days)	20.4	21.9	15.8	***	18.6	25.3	***
Field management labor (days)	66.5	58.2	92.0	***	56.8	59.6	
Harvest labor (days)	24.8	23.9	27.4	**	22.9	25.0	
Mechanization							
Ploughed using power tiller	71	90	12	***	91	89	
Ploughed using tractor	28	10	85	***	8	11	
Cutting & threshing by combine	48	51	38	***	52	51	
Crop cut manually	51	48	59	***	47	49	
Expenses per ha							
Ploughing (GHC)	326	364	210	***	354	373	**
Threshing (GHC)	252	265	210	***	265	265	
Cutting (GHC)	14	11	24	***	13	10	
Transport (GHC)	190	213	117	***	195	232	**
Drying (GHC)	86	84	94		75	92	***
Milling (GHC)	61	71	31	***	51	91	***
No. of observations	1778	1344	434		679	665	

Source: Own computation from World Bank Kpong and Weta irrigation scheme survey.
Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Evidence of Cognitive and Non-Cognitive Traits

	Total	Irrigation Scheme			Crop Establishment Mode (Kpong only)		
		Kpong	Weta		Broadcast	Transplant	
Cognitive skills							
Digitspan	5.6	5.7	5.1	***	5.7	5.8	*
Personality traits							
Achievement Orientation	1.28	1.29	1.26		1.30	1.27	
Power Motivation	0.80	0.84	0.71	**	0.88	0.80	
Tenacity	1.34	1.37	1.26	***	1.37	1.38	
Work Centrality/Passion Composite	1.49	1.47	1.53	*	1.49	1.45	
Internal Locus	-0.15	-0.17	-0.10	*	-0.21	-0.13	*
Optimism	0.62	0.51	0.88	***	0.47	0.56	**
Polychronicity	-0.72	-0.78	-0.58	***	-0.81	-0.76	
Organization	1.39	1.41	1.32	**	1.43	1.40	
Impulsiveness	-0.37	-0.40	-0.30	***	-0.40	-0.40	
Number of Observations	1194	845	349		421	424	

Source: Own computation from World Bank Kpong and Weta irrigation scheme survey.
Asterisks denote significance of t-tests for equality of means between the preceding columns: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Logit Regression for Adoption of Transplanting

	Model			
	All Traits Incl.	**Pre-Selection**	**LARS**	**Stepwise**
Achievement Orientation	-0.028		-0.027	
	(0.322)		(0.306)	
Power Motivation	-0.001			
	(0.959)			
Tenacity	0.032	0.027	0.030	
	(0.147)	(0.200)	(0.163)	
Work Centrality/Passion	-0.066**	-0.072***	-0.066**	-0.048**
	(0.021)	(0.010)	(0.019)	(0.046)
Internal Locus	0.004	0.004	0.005	
	(0.826)	(0.824)	(0.801)	
Optimism	0.043*	0.042*	0.043**	0.050**
	(0.053)	(0.057)	(0.045)	(0.015)
Polychronicity	0.042***	0.044***	0.043***	0.046***
	(0.007)	(0.004)	(0.006)	(0.002)
Organization	0.020	0.019	0.019	
	(0.309)	(0.332)	(0.317)	
Impulsiveness	0.024		0.024	
	(0.362)		(0.371)	
Digitspan	0.011	0.011	0.011	
	(0.294)	(0.300)	(0.308)	
Weta Irrigation Scheme	-0.668***	-0.668***	-0.668***	-0.673***
	(0.000)	(0.000)	(0.000)	(0.000)
Cultivator Age	-0.002*	-0.002*	-0.002*	-0.003**
	(0.082)	(0.088)	(0.057)	(0.027)
Cultivator Education	0.012***	0.012***	0.012***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)
Rice Experience (years)	0.000	0.000		
	(0.890)	(0.853)		
Female	0.065**	0.070**	0.064**	0.061**
	(0.024)	(0.015)	(0.024)	(0.028)
Value of Assets (log)	0.017	0.015	0.018*	
	(0.120)	(0.152)	(0.099)	
Planted Area (log)	0.037	0.039*	0.037	0.049**
	(0.107)	(0.094)	(0.105)	(0.028)
Parcel Fallow Last 5 Years	-0.015	-0.012		-0.017
	(0.844)	(0.876)		(0.822)
Tests for Joint Significance				
All Personality Traits	0.028**	0.010**	0.015**	0.001***
Standard Human Capital Traits	0.000***	0.001***	0.000***	0.000***
Motivational Traits Only	0.103	0.033**	0.048**	0.046**
No. of Observations	1,659	1,659	1,659	1,659

Note: Self-reported soil quality, slope, and presence of erosion control or water harvesting facilities included in all regression but not reported. P-values in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard human capital traits are age, education and experience. Motivational traits are achievement motivation, power motivation, tenacity and work centrality/passion.

Table 5: Elasticities from Stochastic Frontier Translog Production Function

	Model				
	No traits	**All traits**	**Pre-selection**	**LARS**	**Stepwise**
Area (log)	0.460***	0.460***	0.460***	0.461***	0.462***
	0.000	0.000	0.000	0.000	0.000
Value of Pesticide (log)	0.023**	0.025**	0.025**	0.025**	0.025**
	(0.028)	(0.020)	(0.020)	(0.019)	(0.018)
Value of P & K (log)	0.163***	0.164***	0.163***	0.162***	0.161***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Value of N (log)	0.178***	0.180***	0.179***	0.179***	0.179***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cost of Threshing/ha (log)	0.075	0.068	0.067	0.069	0.070
	(0.305)	(0.362)	(0.367)	(0.353)	(0.347)
Cost of Ploughing/ha (log)	0.231***	0.225***	0.226***	0.225***	0.227***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Labor Days (log)	-0.014	-0.011	-0.011	-0.010	-0.011
	(0.240)	(0.370)	(0.366)	(0.396)	(0.341)
Parcel Fallow Last 5 years	-0.185***	-0.177***	-0.177***	-0.180***	-0.179***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Soil Quality Fair	-0.082***	-0.079***	-0.079***	-0.079***	-0.078***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Soil Quality Poor	-0.410***	-0.402***	-0.402***	-0.400***	-0.399***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	4.510***	4.634***	4.635***	4.633***	4.612***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 5 (cont'd): Inefficiency Parameters from the Stochastic Frontier Translog Production Function

	Model				
	No traits	**All traits**	**Pre-selection**	**LARS**	**Stepwise**
Achievement Orientation		-0.626	-0.645	-0.558	-0.517
		(0.226)	(0.207)	(0.256)	(0.258)
Power Motivation		0.288	0.308	0.272	
		(0.309)	(0.263)	(0.298)	
Tenacity		-0.230	-0.229	-0.205	
		(0.557)	(0.557)	(0.589)	
Work Centrality/Passion		-1.080**	-1.105**	-0.963**	-0.917**
		(0.026)	(0.020)	(0.029)	(0.025)
Internal Locus		0.255	0.216		
		(0.480)	(0.529)		
Optimism		-0.145			
		(0.721)			
Polychronicity		-0.970***	-0.955***	-0.914***	-0.852***
		(0.001)	(0.001)	(0.001)	(0.001)
Organization		0.348	0.327		
		(0.348)	(0.370)		
Impulsiveness		0.528	0.526		
		(0.282)	(0.281)		
Digit Span		-0.297	-0.296	-0.271	-0.295*
		(0.116)	(0.116)	(0.131)	(0.069)
Weta Dummy	2.513***	2.081***	2.020***	1.995***	2.676***
	(0.009)	(0.005)	(0.005)	(0.004)	(0.000)
Cultivator Age	0.003	-0.010	-0.010		
	(0.927)	(0.616)	(0.625)		
Cultivator Education	-0.072	-0.032	-0.033	-0.030	
	(0.271)	(0.530)	(0.517)	(0.544)	
Cult. Experience	0.016	0.022	0.022	0.017	
	(0.684)	(0.443)	(0.442)	(0.478)	
Female Cultivator	1.425**	0.929*	0.919*	0.875*	0.890**
	(0.035)	(0.064)	(0.066)	(0.065)	(0.038)
No. HH Members (log)	1.181**	0.909**	0.901**	0.888**	0.933**
	(0.033)	(0.026)	(0.026)	(0.023)	(0.015)
Transplanting Used	-3.619***	-2.594***	-2.588***	-2.461***	-2.510***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tests for joint significance					
All Personality Traits		0.011**	0.006***	0.002***	0.001***
Standard Human Capital Traits	0.655	0.795	0.823	0.689	
Motivational Traits Only		0.032**	0.018**	0.024**	0.009***
No. of Observations	1,778	1,778	1,778	1,778	1,778
/Usigma	1.502	1.163	1.160	1.134	1.122
	(0.128)	(0.103)	(0.102)	(0.105)	(0.106)
/Vsigma	-2.791***	-2.777***	-2.778***	-2.790***	-2.802***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

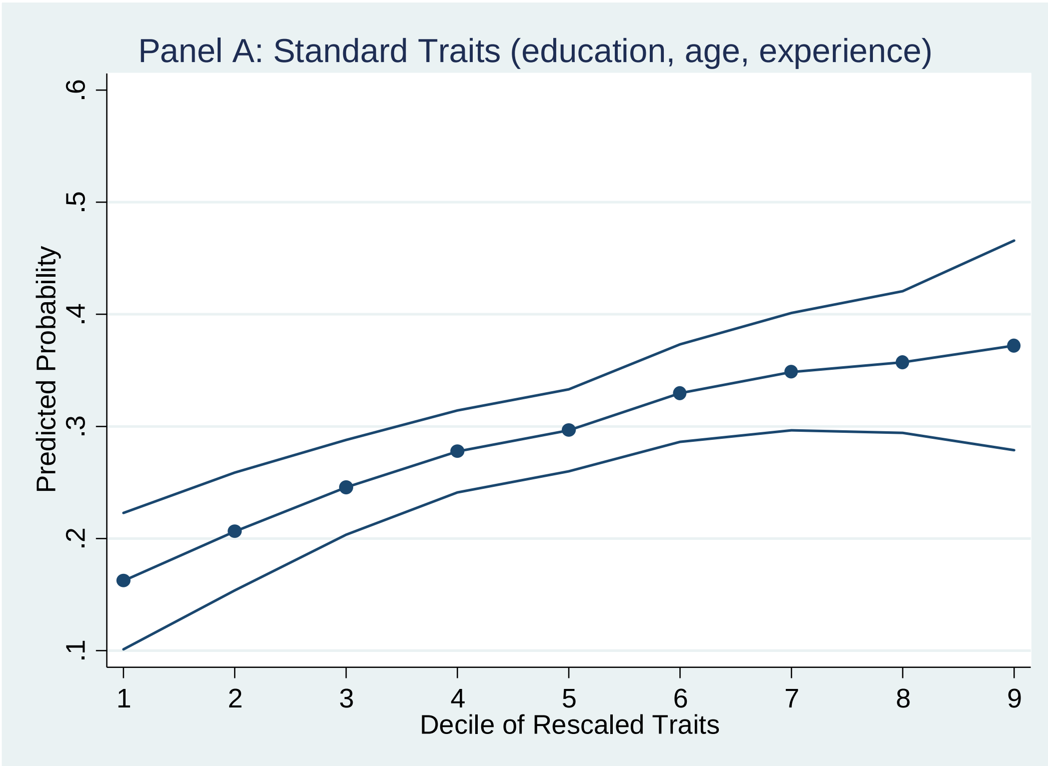
Note: Indicators of seed type and parcel's tenure status included throughout but not reported. Likelihood ratio p-values in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard human capital traits are age, education and experience. Motivational traits are achievement motivation, power motivation, tenacity and work centrality/passion.

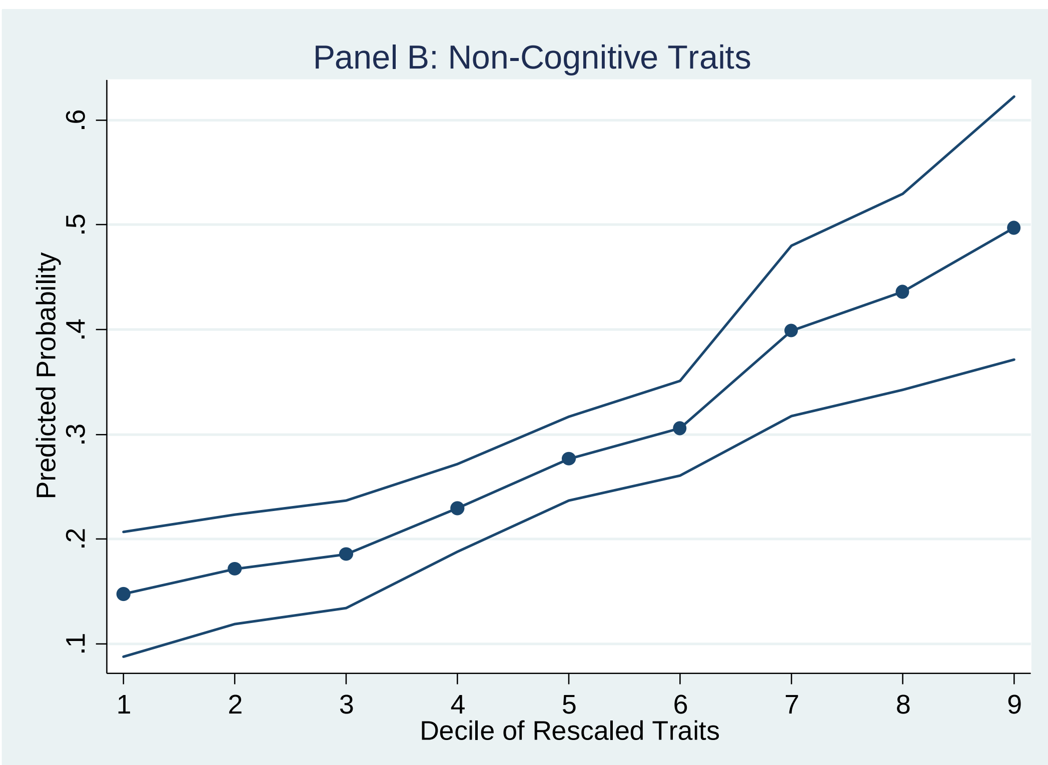
Table 6: Inefficiency Parameters from Non-Neutral Stochastic Frontier Translog Production Function

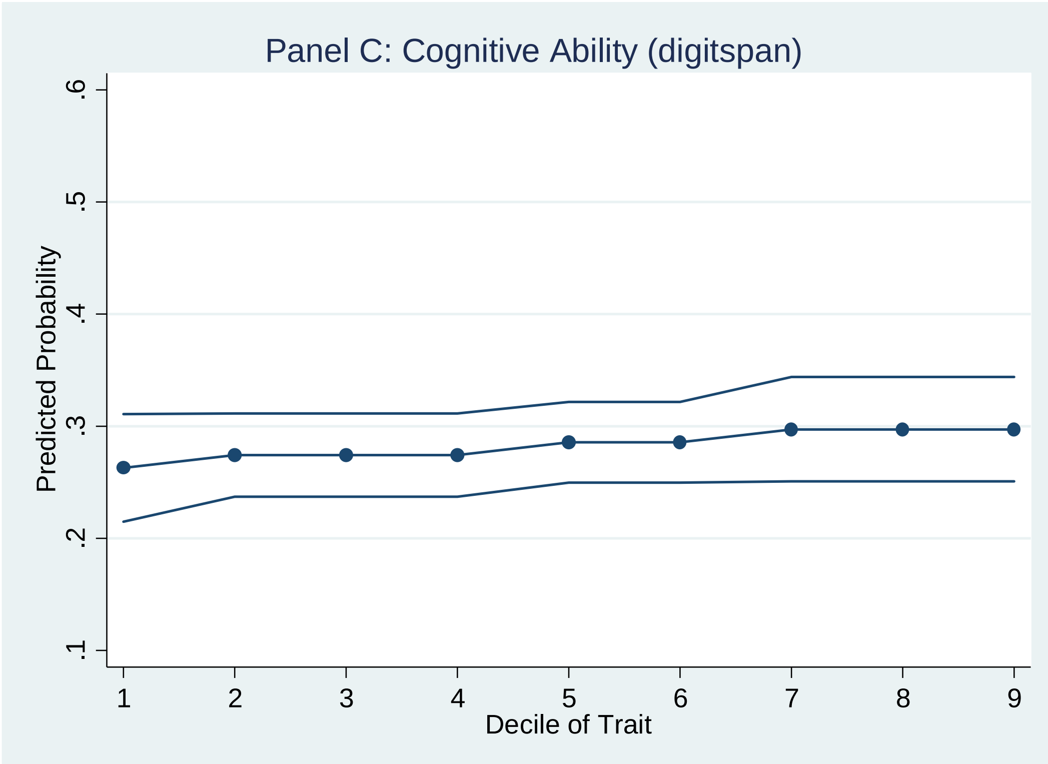
	Marginal Effect	Interaction with Transplant Adoption
Inefficiency Parameters		
Transplanting Technique Used	0.507***	
	(0.000)	
Impulsiveness	0.058	-0.349
	(0.424)	(0.357)
Tenacity	-0.066	0.190
	(0.517)	(0.539)
Polychronicity	-0.208***	0.291
	(0.002)	(0.228)
Internal Locus	0.101	-0.356
	(0.181)	(0.197)
Achievement Orientation	-0.260**	-0.870**
	(0.030)	(0.032)
Power Motivation	-0.056***	-0.539**
	(0.009)	(0.028)
Organization	0.158	0.179
	(0.411)	(0.527)
Optimism	-0.128	-0.250
	(0.590)	(0.446)
Work Centrality/Passion	-0.265**	0.477
	(0.017)	(0.195)
Digitspan	-0.161**	-0.231
	(0.025)	(0.133)
Weta Irrigation Scheme	1.184***	0.677
	(0.000)	(0.553)
Primary Cultivator Age	-0.010	-0.029
	(0.259)	(0.142)
Primary Cultivator Education	0.008	0.066
	(0.236)	(0.129)
Primary Cultivator Experience	0.007	0.032
	(0.444)	(0.236)
Female Primary Cultivator	0.305	0.248
	(0.158)	(0.498)
No. HH Members (log)	0.458***	0.931**
	(0.008)	(0.041)
Tests for joint significance		
All Interactions with Transplant Adoption		0.000***
All Personality Traits	0.006***	0.065**
Standard Human Capital Traits	0.315	0.108
Motivational Traits Only	0.006***	0.018**
Number of Observations	1,778	1,778
/Usigma	-0.037	-0.091
	0.880	0.698
/Vsigma	-2.835***	-2.797***
	0.000	0.000

Note: Marginal effects are reported at the mean. Likelihood ratio p-values are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard human capital traits are age, education and experience. Motivational traits are achievement motivation, power motivation, tenacity and work centrality/passion. Indicators of seed type, and parcel's tenure status included but not reported.

Figure 1: Predicted probability of transplant adoption by decile of traits in the sample with 95% confidence intervals






Panel C: Cognitive Ability (digitspan)
Predicted Probability
.1
.2
.3
.4
.5
.6
1
2
3
4
5
6
7
8
9
Decile of Trait

Appendix: Entrepreneurial Psychology Survey Questions following McKenzie & Woodruff (2010)

Responses to all questions are on a scale of one to five, with five indicating “agree strongly” and one indicating “disagree strongly.”

1. Impulsiveness:
I plan tasks carefully (scale reversed).
I make up my mind quickly.
I save regularly (scale reversed).

2. Tenacity:
I can think of many times when I persisted with work when others quit.
I continue to work on hard projects even when others oppose me.

Polychronicity:
I like to juggle several activities at the same time.
I would rather complete an entire project every day than complete parts of several projects (scale reversed).
I believe it is best to complete one task before beginning another (scale reversed).

3. Locus of control:
It is difficult to know who my real friends are (scale reversed)
I never try anything that I am not sure of (scale reversed)
A person can get rich by taking risks

4. Achievement:
It is important for me to do whatever I’m doing as well as I can even if it isn’t popular with people around me.
Part of my enjoyment in doing things is improving my past performance.
When a group I belong to plans an activity, I would rather direct it myself than just help out and have someone else organize it.
I try harder when I’m in competition with other people.
It is important to me to perform better than others on a task.
I try harder when I’m in competition with other people.
It is important to me to perform better than others on a task.

5. Power motivation:
I enjoy planning things and deciding what other people should do.
I find satisfaction in having influence over others.
I like to have a lot of control over the events around me.

6. Passion for work/work centrality:
I look forward to returning to my work when I am away from work.
The most important thing that happens in life involves work.
It is important for me to do whatever I’m doing as well as I can even if it isn’t popular with people around me.
Part of my enjoyment in doing things is improving my past performance.

7. Organized person:
My family and friends would say I am a very organized person.

8. Optimism:
In uncertain times I usually expect the best.
If something can go wrong for me, it will (scale reversed).
I’m always optimistic about my future.
I hardly ever expect things to go my way (scale reversed).
I rarely count on good things happening to me (scale reversed).
* The attitude variables are constructed by rescaling each question from -2 to 2. The questions within each attitude category are then summed and divided by the number of questions to produce an indicator of range [-2,2].

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