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

DANIEL AYALEW ALI*, DERICK BOWEN** & KLAUS DEININGER*

*Development Research Group, World Bank, Washington, DC, USA, **Economic Analysis Division, Department of Policy and Evaluation, Millennium Challenge Corporation, Washington, DC, USA

(Original version submitted September 2018; final version accepted September 2019)

ABSTRACT Although a large literature highlights the impact of personality traits on key labour 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.

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, Just, & Zilberman, 1985) highlights determinants of technology adoption, including cognitive ability to assess payoffs from different options, social networks to access information (Conley & Udry, 2010), the ability to bear or insure against risks, and access to capital.

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, self-discipline has been found to be more important than standard indicators such as IQ (Duckworth & Seligman, 2005). They also have been found to be significant predictors of healthy behaviour 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 labour market and health outcomes (Heckman, Moon, Pinto, Savelyev, & Yavitz, 2010).

Correspondence Address: Derick Bowen, Millennium Challenge Corporation, Washington, DC, USA. Email: bowenfh@mcc.gov

Supplementary Materials are available for this article which can be accessed via the online version of this journal available at https://doi.org/10.1080/00220388.2019.1666978

© International Bank for Reconstruction and Development/The World Bank 2019
Conceptual models illustrate 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 & Lueck, 1998). Personality traits are therefore likely to be important determinants of agricultural technical efficiency and technology adoption and may only weakly correlate with traditional measures of human capital. Despite the often limited explanatory power of traditional human capital measures in adoption regressions (Huffman, 2001), there has been little study of personality traits’ relevance to these outcomes.

As a 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 labour 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 labour demands in the 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 that had been 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 related to the adoption decision and efficiency of input use. In sum, non-cognitive skills that thus far have received limited attention from agricultural economists are important predictors of producers’ technical efficiency as well as their adoption decisions and adoption outcomes. These findings show that greater attention to 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.

2. Can personality traits explain smallholder technology adoption and agricultural productivity?

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 & Rosenzweig, 2010) that highlight the importance of prior adoption decisions and outcomes of farmers within an agent’s network (Conley & Udry, 2010; Liverpool-Tasie & Winter-Nelson, 2012; Krishnan & Patnam, 2014). Explicit investigation of the relationship between personality traits and smallholder technology adoption, however, has been scant.

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, Duckworth, Heckman, & Weel, 2008). The psychology literature defines the latter as ‘relatively enduring patterns of thoughts, feelings, and behaviours that reflect the tendency to respond in certain ways under certain circumstances’ (Roberts, 2009), a definition used in recent literature, such as Almlund, Duckworth, Heckman, and Kautz (2011), aiming to bridge personality psychology and economics. In practice, the
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 & 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 organisation 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 & Ashton, 2001; Roberts, Chernyshenko, Stark, & Goldberg, 2005).

A surge of recent research has found non-cognitive skills and personality traits to be powerful predictors of schooling and labour market success with a predictive ability equal or superior to that of cognitive skills (Blanden, Gregg, & Macmillan, 2007; Heckman & Rubinstein, 2001; Heckman, Stixrud, & Urzua, 2006; Heineck & Anger, 2010). For example, a longitudinal study for the US shows that moving an individual from the 25th to the 75th 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 & Rubinstein, 2001). The Perry preschool programme, 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 & Seligman, 2005). Studies find non-cognitive skills to predict risk taking, violence, illegal activities, smoking and drinking (Carneiro, Crawford, & Goodman, 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). 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, McKenzie, & Woodruff, 2009) and default for micro-loan applicants (Klinger, Khwaja, & Del Carpio, 2013).

Similarly, non-cognitive skills may be important determinants of smallholder technology adoption and agricultural productivity. 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 smallholder 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 characterise the study setting, which is dynamic and well integrated with peri-urban labour 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, 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, the sample includes 1,194 cultivators with 1,778 rice parcels.

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. The average cultivator is 46 years old with 9 years of formal education. The share of cultivators who can read and write is 67 per cent. Most sampled farmers’ primary occupation is agriculture (89%). Still, the diversified nature of the environment is illustrated by the fact that 53 per cent have access to non-farm enterprise income, and 31 per cent 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 mechanisation. 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). Net revenue per ha, after subtracting hired labour, non-labour inputs and expenses related to ploughing and harvesting, is also statistically significantly higher in Kpong (GHC 2,359) than in Weta (GHC 437). For 74 per cent of parcels, the cultivator has the use

### Table 1. Farmer-level characteristics

|                      | Irrigation scheme | Crop establishment mode (Kpong only) |
|----------------------|-------------------|-------------------------------------|
|                      | Total  | 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.

*Notes*: Asterisks denote significance of t-tests for equality of means between the preceding columns: ***p < 0.01, **p < 0.05, *p < 0.1.
rights, having acquired them on average 24 years ago. Land use rights are allocated by the government and non-transferable except through inheritance. Although leasing in contravention of the official regulations is widespread, affecting some 26 per cent of sampled parcels, it does not seem to deter transplanting; in fact, 30 per cent of transplanted parcels are 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 per cent higher, while the value of insecticide and fungicide per hectare is

| Table 2. Parcel level characteristics |
|---------------------------------------|
| **Irrigation scheme** | **Crop establishment mode** |
| | **Total** | **Kpong** | **Weta** | **Broadcast** | **Transplant** |
| Harvest per hectare (Kg) | 4572 | 5033 | 3143 | *** | 4756 | 5315 | *** |
| Value of yield per hectare (GHC)\(a\) | 4486 | 5033 | 2794 | *** | 4756 | 5315 | *** |
| Net revenue per ha (GHC)\(b\) | 1892 | 2359 | 437 | *** | 2265 | 2455 | *** |

**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-Labour 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 | |

**Labour inputs**

| Male family labour/ha (days) | 24.8 | 24.2 | 26.4 | | 25.2 | 23.3 | |
| Female family labour/ha (days) | 17.8 | 14.5 | 27.9 | *** | 15.1 | 14.0 | |
| Male child family labour/ha (days) | 6.4 | 5.1 | 10.3 | *** | 6.2 | 4.0 | * |
| Fem. Child family labour/ha (days) | 3.9 | 3.3 | 5.6 | ** | 4.3 | 2.3 | ** |
| Male hired labour/ha (days) | 30.5 | 34.0 | 19.6 | *** | 28.9 | 39.3 | *** |
| Female hired labour/ha (days) | 25.3 | 19.7 | 42.6 | *** | 16.7 | 22.8 | *** |
| Land preparation labour (days) | 20.4 | 21.9 | 15.8 | *** | 18.6 | 25.3 | *** |
| Field management labour (days) | 66.5 | 58.2 | 92.0 | *** | 56.8 | 59.6 | |
| Harvest labour (days) | 24.8 | 23.9 | 27.4 | ** | 22.9 | 25.0 | |

**Mechanisation**

| 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.
Notes: Asterisks denote significance of t-tests for equality of means between the preceding columns: ***p < 0.01, **p < 0.05, *p < 0.1. aPrice of rice was, on average, GHC 1 in Kpong and GHC 0.9 in Weta at the time of the survey. bComputed by subtracting the value of non-labour inputs, labour inputs (excluding family labour) and expenses on ploughing and harvesting (including imputed rentals for owned machinery and transport costs) from the value of crop output.
76 per cent and 80 per cent lower, respectively. Inorganic fertiliser use is widespread, though less than 5 per cent use organic fertiliser. Applying formulas to compute pure nutrients points towards little difference in N application but slightly lower levels of P in Weta. Also, with 3 per cent of producers practicing it, transplanting is less common in Weta than in Kpong (49%).

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 labour 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 (cols. 4 and 5 of Table 2) with a yield difference of 12 per cent (or 0.56 t/ha) and a net revenue per ha difference of 8 per cent (GHC 190) in Kpong. Columns 4 and 5 of Tables 1 and 2 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 per cent less on seed per hectare (262 GHC vs 151 GHC), use 36 per cent more labour on land preparation (25.3 vs 18.6 days/ha) but, presumably due to higher yields, use similar levels of labour for field management and harvest. Male and female cultivators are equally likely to use transplanting to establish their crop.

Mechanised 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 per cent 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%). In both locations, most harvest labour is hired. Overall, cultivators report 119 days between completion of planting and completion of harvest. Despite lower yields, the number of labour days spent is about 30 per cent higher in Weta than in Kpong, with a higher share of days allocated to crop management.

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 the Supplementary Materials together with the relevant groupings, are identical to those in De Mel, McKenzie, and Woodruff (2010). 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 9 categories are summed up and divided by the number of responses per category to obtain an indicator in the [−2, 2] range.

The first four traits, as presented in Table 3, can be conceptualised 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 & Locke, 2004; building on Gartner, Gatewood, & Shaver, 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, Ghosh, & Kanungo, 1990) and work passion is a measure of love or passion for one’s work (Locke, 2000).

Personal beliefs, on the other hand, 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. Finally, traits related to how individuals approach work tasks are polychronicity, organisation and impulsiveness. Polychronicity refers to the preference of individuals to simultaneously participate in multiple tasks or events (Bluedorn, Kalliath, Strube, & Martin, 1999). Organisation 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, Stanford, & Barratt, 1995). Frederick, Loewenstein, and O’donoghue (2002) argue that, along with compulsivity and inhibition, impulsiveness is one of 3 subdimensions of the time preference parameter commonly estimated by economists.

The non-cognitive skill questions were administered at the end of the interview to ensure respondents had time to develop comfort with the interview. Laajaj and Macours (2017) recently found that non-cognitive skill measurements in rural Kenya were substantially more reliable (as measured by test–retest correlation) when administered at the end of interviews, and that survey fatigue had no effect on responses to cognitive and non-cognitive questions.

To test for acquiescence bias, we follow the procedure of Soto, John, Gosling, and Potter (2008) in summing the positively and negatively phrased question pairs that are most similar (before the negatively phrased questions are reversed) and dividing by the number of questions to calculate an acquiescence score. We find clear evidence of acquiescence bias with a mean bias of 0.84. The psychometric literature has found that acquiescence bias tends to be higher for individuals with lower education levels (e.g., Ayidiya & McClendon, 1990; Narayan & Krosnick, 1996; Rammstedt & Farmer, 2013; Rammstedt, Goldberg, & Borg, 2010; Rammstedt et al., 2010; Rammstedt & Kemper, 2011). We find a pairwise correlation between acquiescence bias and primary cultivator education of −0.04, although this is statistically insignificant. To test the robustness of the main results to acquiescence bias, acquiescence adjusted versions of each trait indicator were also therefore constructed. To do so, the acquiescence score was subtracted from each of the non-cognitive questions before they were reversed, and the responses in each of the 9 categories then summed up and divided by the number of responses per category.

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 trans-planters in Kpong. It points towards significant differences between the two irrigation schemes.

| Cognitive skills               | Irrigation scheme | Crop establishment mode (Kpong only) |
|-------------------------------|-------------------|-------------------------------------|
|                               | Total  | Kpong  | Weta | Broadcast | Transplant |
| Digitspan                     | 5.6    | 5.7    | 5.1  | 5.7       | 5.8        | *               |

Table 3. Evidence of cognitive and non-cognitive traits

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

3.3. Exploring impacts of personality traits on technology adoption

To assess factors that may contribute to adoption of transplanting or mechanised 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); (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, Morris, Davis, & Davis, 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 and locus of control to positively associate with perceptions related to all four determinants and in turn adoption. High levels of polychronicity and organisation 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. Likewise, we expect 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. Since digitspan measures individuals’ ability to process new information and learning, which has been shown to be essential for adoption of complex technologies (Foster & 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 first proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van Den Broeck (1977) to analyse 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 \( \mu = \delta_i Z_i + \epsilon \), where \( \epsilon \) is a normally distributed error term with mean zero that is truncated from below at \(-\delta_i Z_i\) (so that \( \mu \) 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:

\[
\ln(Y) = \sum_i \beta_i \ln(X_i) + \frac{1}{2} \sum_i \sum_j \beta_{ij} \ln(X_i) \ln(X_j) + \theta_k G_k - \mu + \nu
\]
where $Y$ is yield per hectare; $X_i$ are physical inputs including the area of land planted, the amount of labour, nitrogen and phosphate applied per hectare, and the cost of crop protection chemicals (herbicide, insecticide and fungicide), mechanised ploughing and mechanised 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 $\mu$ is defined as above by $\mu = \delta Z_i + \varepsilon$ 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. $\varepsilon$ is normally distributed with mean zero, but truncated from below at $-\delta Z_i$.  

In addition to the conventional factors included in regressions of this type (Liu & Myers, 2009; Sherlund, Barrett, & Adesina, 2002), previous research has linked motivational traits (Dunifon & Duncan, 1998), locus of control (Groves, 2005; Heckman et al., 2006), and organisation with labour 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 synchronise multiple income streams. Higher discount rates in early life, due to impulsiveness, have been shown to negatively impact later life success (Castillo, Ferraro, Jordan, & Petrie, 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 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). 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 and least angle regression (Efron, Hastie, Johnstone, & Tibshirani, 2004) 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 per cent level for the first 3 models, and at the 1 per cent 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 per cent in all specifications. Optimism is significant at 10 per cent or 5 per cent, except when introduced
independently, where it is insignificant. Work centrality/passion is negatively associated with adoption of transplanting, possibly because of a more traditionalist attitude. This relationship is significant at 5 per cent or 1 per cent, except when introduced independently, where it is insignificant. For the adoption of mechanised 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.

Table 4. Logit regression for adoption of transplanting

| Model                      | All traits Incl. | Pre-selection | LARS    | Stepwise |
|----------------------------|------------------|---------------|---------|----------|
| Achievement orientation    | -0.028           | -0.027        | -0.027  | (0.322)  |
|                            | (0.959)          |               |         |          |
| Power motivation           | -0.001           | 0.004         | 0.004   | (0.826)  |
|                            | (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)  |
| Organisation              | 0.020            | 0.019         | 0.019   | (0.309)  |
|                            | (0.332)          |               |         | (0.317)  |
| Impulsiveness             | 0.024            | 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         | 0.000   | (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  | -0.017   |
|                            | (0.844)          | (0.876)       | (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

Notes: 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.
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.\textsuperscript{24} The 95 per cent 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.\textsuperscript{25} At the same time, predicted marginal impacts decrease rapidly when moving up the distribution,\textsuperscript{26} with marginal gains from higher levels of education negligible beyond the 3\textsuperscript{rd} or 4\textsuperscript{th} 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 1\textsuperscript{st} to the 9\textsuperscript{th} 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 1\textsuperscript{st} to the 9\textsuperscript{th} decile of the distribution of non-cognitive skills is more than double that of standard human capital measures. While this is of course not a causal estimate and agricultural

Figure 1. Predicted probability of transplant adoption by decile of traits in the sample with 95% confidence intervals.
productivity may affect human capital (Almlund et al., 2011), concerns about such reverse causality for non-cognitive skills are further reduced by the fact that both irrigation schemes were developed and settled only recently.

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 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. 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 labour days, which may point towards application of labour 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 fertiliser and other chemicals is widespread.

The second part of Table 5 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 per cent in all specifications. Likewise, household size is estimated to be a significant determinant of efficiency regardless of specification, suggesting labour market imperfections. Finally, personality traits are jointly significant at 5 per cent when including all traits and 1 per cent 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 per cent and 5 per cent, 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 per cent 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 per cent to 67 per cent. Based on our production function, this would translate to a 0.9 per cent 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 per cent to 68.5 per cent, equivalent to a 6.2 per cent output increase or an income gain of GHC 268 (USD 139) per hectare and season. With two irrigated seasons per year and a 12 per cent 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).
Table 5. (a) Elasticities from stochastic frontier translog production function. (b) Inefficiency parameters from the stochastic frontier translog production function

| Model | No traits | All traits | Pre-selection | LARS | Stepwise |
|-------|-----------|------------|---------------|------|----------|
| (a)   |           |            |               |      |          |
| Area (log) | 0.460*** (0.000) | 0.460*** (0.000) | 0.460*** (0.000) | 0.461*** (0.000) | 0.462*** (0.000) |
| Value of pesticide (log) | 0.023** (0.028) | 0.025** (0.020) | 0.025** (0.020) | 0.025** (0.019) | 0.025** (0.018) |
| Value of P & K (log) | 0.163*** (0.000) | 0.164*** (0.000) | 0.163*** (0.000) | 0.162*** (0.000) | 0.161*** (0.000) |
| Value of N (log) | 0.178*** (0.000) | 0.180*** (0.000) | 0.179*** (0.000) | 0.179*** (0.000) | 0.179*** (0.000) |
| Cost of threshing/ha (log) | 0.075 (0.305) | 0.068 (0.362) | 0.067 (0.367) | 0.069 (0.353) | 0.070 (0.347) |
| Cost of ploughing/ha (log) | 0.231*** (0.000) | 0.225*** (0.000) | 0.226*** (0.000) | 0.225*** (0.000) | 0.227*** (0.000) |
| Labour days (log) | -0.014 (0.240) | -0.011 (0.370) | -0.011 (0.366) | -0.010 (0.396) | -0.011 (0.341) |
| Parcel fallow last 5 years | -0.185*** (0.002) | -0.177*** (0.004) | -0.177*** (0.004) | -0.180*** (0.003) | -0.179*** (0.003) |
| Soil quality fair | -0.082*** (0.001) | -0.079*** (0.002) | -0.079*** (0.002) | -0.079*** (0.002) | -0.078*** (0.002) |
| Soil quality poor | -0.410*** (0.000) | -0.402*** (0.000) | -0.402*** (0.000) | -0.400*** (0.000) | -0.399*** (0.000) |
| Constant | 4.510*** (0.000) | 4.634*** (0.000) | 4.635*** (0.000) | 4.633*** (0.000) | 4.612*** (0.000) |
| (b)    |           |            |               |      |          |
| Achievement orientation | -0.626 (0.226) | -0.645 (0.207) | -0.558 (0.256) | -0.517 (0.258) |
| Power motivation | 0.288 (0.309) | 0.308 (0.263) | 0.272 (0.298) |
| Tenacity | -0.230 (0.557) | -0.229 (0.557) | -0.205 (0.589) |
| Work centrality/Passion | -1.080*** (0.026) | -1.105** (0.020) | -0.963** (0.029) | -0.917** (0.025) |
| Internal locus | 0.255 (0.480) | 0.216 (0.529) |
| Optimism | -0.145 (0.721) |
| Polychronicity | -0.970*** (0.001) | -0.955*** (0.001) | -0.914*** (0.001) | -0.852*** (0.001) |
| Organisation | 0.348 (0.348) | 0.327 (0.370) |
| Impulsiveness | 0.528 (0.282) | 0.526 (0.281) |
| Digit span | -0.297 (0.116) | -0.296 (0.116) | -0.271 (0.131) | -0.295* (0.069) |
| Weta dummy | 2.513*** (0.009) | 2.081*** (0.005) | 2.020*** (0.005) | 1.995*** (0.004) | 2.676*** (0.000) |
| Cultivator age | 0.003 (0.927) | -0.010 (0.616) | -0.010 (0.625) |
| Cultivator education | -0.072 (0.271) | -0.032 (0.530) | -0.033 (0.517) | -0.030 (0.544) |
| Cult. Experience | 0.016 (0.684) | 0.022 (0.443) | 0.022 (0.442) | 0.017 (0.478) |
| Female cultivator | 1.425** (0.875) | 0.929* (0.890) | 0.919* (0.890) |

(continued)
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 per cent 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

| Table 5. (continued) |
|----------------------|
| Model                |
|                      | No traits | All traits | Pre-selection | LARS       | Stepwise   |
| No. HH members (log) |           |           |              |            |            |
|                      | (0.035)   | (0.064)   | (0.066)      | (0.065)    | (0.038)    |
|                      | 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 | 0.655     | 0.795     | 0.823        | 0.689      |            |
| Standard human capital traits | 0.011**   | 0.006***  | 0.002***     | 0.010***   |            |
| Motivational traits only | 0.322**   | 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)    |

Notes: 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.
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 6. Inefficiency parameters from non-neutral stochastic frontier translog production function

| Inefficiency parameters                        | Marginal effect | Interaction with transplant adoption |
|-----------------------------------------------|-----------------|-------------------------------------|
| 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)               |
| Organisation                                 | 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

Notes: 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.
Acknowledgments

We are grateful to Iggy Bassi, Toks Abimbola, and Karan Chopra in GADCO’s management team for their support to this research, Julius Ameku, Sridhar Reddy, and Vishnuvardhan Banda for field implementation, Markus Goldstein, Tricia Koroknay-Palicz, Angeli Kirk, Courtney Han, Francesca Viola, and Junwei Chen at the World Bank for comments and contributions to the data collection. We thank the IPA Ghana team for excellent fieldwork, particularly Gabriel Lawin, Dziwornu Kwami Adanu, Mona Niina Iddrisu, Virginia Ceretti, Cornelius Owusu Adjei, Maham Farhat, Nicolas Marin, James Svenstrup, Philip Amara, Pace Philips, and Loic Watine. We appreciate cooperation and support from the Ghana Irrigation Development Authority (GIDA). Financial support from a USAID Trust Fund to support impact evaluation of initiatives under the GCAP project, and the Africa region PSIA Trust Fund is gratefully acknowledged. The analysis data and code can be made available to bona fide researchers on request.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Poverty and Social Impact Analysis (PSIA) Multi-Donor Trust Fund [TF014128: Evaluating and Enhancing Local Benefits].

Notes

1. Throughout the paper, we refer to ‘personality traits’ as comprising both personality and motivation traits.
2. All female farmers were included to allow sufficient statistical power for analysis by gender sub-group.
3. 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.
4. 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.
5. Cultivators located in Weta apply 30 per cent 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.
6. 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.
7. They find a test–retest correlation of 0.73 when non-cognitive skill questions were administered at the end of the interview, just above the minimum of 0.7 often applied to define reliability.
8. Acquiescence bias is the tendency of some respondents to agree with the contents of a question regardless of the content. Since the non-cognitive skill response categories include an unequal number of positively and negatively phrased questions, the trait indicator values may reflect both the underlying trait and the extent of the respondent’s acquiescence bias (Laajaj & Macours, 2017; Rammstedt & Farmer, 2013; Soto et al., 2008).
9. Due to the structure of our instrument, similar positively and negatively phrased questions were not available for each trait category. The question pairs used for the correction are identified in the Supplementary Materials.
10. P-value < 0.0001.
11. P-value = 0.1629.
12. While some psychometric studies have also applied ipsatization (dividing by the standard deviation of all responses after subtracting the mean), this practice is debated in psychometric literature, and was found by (Laajaj & Macours, 2017) to worsen the validity and reliability of non-cognitive constructs. We do not apply it here.
13. While the literature suggests that the factor analysis deriving the Big Five Factor structure can be replicated across cultures (McCrae & Costa, 1997), personality indicators for individuals may vary systematically across areas due to environmental or cultural characteristics (see, McCrae & Terracciano, 2005).
This could also be understood as a reversed scale of the perceived cost of adoption.

This is also consistent with recent theoretical and empirical research highlighting the importance of internal constraints such as perceived self-efficacy (Wuepper & Lybbert, 2017) and hope (Lybbert & Wydick, 2018) to recognising investment opportunities, with important implications for poverty and economic development.

The maximum likelihood estimation is performed in STATA 13 using the sfx command (Belotti, Daidone, Ilardi, & Atella, 2012). Likelihood ratio tests are used to test for significance of the Z terms.

Psychology literature on farmers’ stress consistently shows time management to be a leading factor (Alpass et al., 2004; J. Deary, Willock, & McGregor, 1997; McGregor, Willock, & Deary, 1995; Pollock, Deaville, Gilman, & Willock, 2002; Walker & Walker, 1987).

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, Anderson, Tatham, and Black (1995) suggest that a VIF below 10 indicates inconsequential collinearity.

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 outcome variable that 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.

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).

To test for robustness, we also remove traits with Cronbach’s alpha scores below 0.4 and repeat the above procedure. The Cronbach’s alpha scores range from 0.41 to 0.61 for the unadjusted traits, and 0.61–0.81 for the acquiescence bias adjusted traits with the exception of impulsiveness and locus of control, which are removed for the robustness check.

These results are unaffected by either adjustment for acquiescence bias (Supplementary Material Table 1), or removal of traits with a low Cronbach’s alpha score (Supplementary Material Table 3).

Results for mechanised harvest adoption are available from the authors on request.

To allow consistent interpretation, values for traits with negative coefficients are re-scaled so that higher deciles increase centrality/passion and age are reversed.

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 digit span as a possibly more accurate measure of cognitive ability (panel C). All other covariates are held constant at their sample means and the 95 per cent confidence band is computed using the delta method.

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

The Cobb-Douglas is rejected in favour of the translog at the 1 per cent level for specifications both with and without non-cognitive traits.

When estimated on the acquiescence bias adjusted traits (Supplementary Material Table 2), the coefficient on work centrality/passion reduces by a third and becomes insignificant in some specifications, while the coefficients on power motivation, organisation and optimism increase and become significant in some specifications. Removal of traits with a low Cronbach’s alpha score (Supplementary Material Table 4) does not affect the results.

References

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21–37.

Allen, D., & Lueck, D. (1998). The nature of the farm. *Journal of Law and Economics*, 41(2), 343–386.

Almlund, M., Duckworth, A. L., Heckman, J. J., & Kautz, T. D. (2011). Personality psychology and economics. In *Handbook of the Economics of Education* (Vol. 4, pp. 1–181). Elsevier.

Alpass, F., Flett, R., Humphries, S., Massey, C., Morriss, S., & Long, N. (2004). Stress in dairy farming and the adoption of new technology. *International Journal of Stress Management*, 11(3), 270–281.

Ayidiya, S. A., & McClendon, M. J. (1990). Response effects in mail surveys. *Public Opinion Quarterly*, 54, 229–247.
Klinger, B., Khwaja, A. I., & Del Carpio, C. (2013). Enterprising psychometrics and poverty reduction. New York, NY: Springer.

Krishnan, P., & Patnam, M. (2014). Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? American Journal of Agricultural Economics, 96(1), 308–327.

Laaajj, R., & Macours, K. 2017. Measuring skills in developing countries. The World Bank, Policy Research Working Paper Series 8000.

Liu, Y., & Myers, R. (2009). Model selection in stochastic frontier analysis with an application to maize production in Kenya. Journal of Productivity Analysis, 31(1), 33–46.

Liverpool-Tasie, L. S. O., & Winter-Nelson, A. (2012). Social learning and farm technology in Ethiopia: Impacts by technology, network type, and poverty status. Journal of Development Studies, 48(10), 1505–1521.

Locke, E. (2000). Motivation, cognition, and action: An analysis of studies of task goals and knowledge. Applied Psychology, 49(3), 408–429.

Lybbert, T. J., & Wydick, B. (2018). Poverty, aspirations, and the economics of hope. Economic Development and Cultural Change, 66(4), 709–753.

McClelland, D. C. (1985). How motives, skills, and values determine what people do. American Psychologist, 40(7), 812.

McCrae, R. R., & Costa, P. T. (1997). Personality trait structure as a human universal. American Psychologist, 52(5), 509–516.

McCrae, R. R., & Terracciano, A. (2005). Personality profiles of cultures: Aggregate personality traits. Journal of Personality and Social Psychology, 89(3), 407–425.

McGregor, M., Willock, J., & Deary, I. (1995). Farmer stress. Farm Management, 9, 57–65.

Meuesen, W., & Van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. International Economic Review, 18, 435–444.

Misra, S., Ghosh, R., & Kamungo, R. N. (1996). Measurement of family involvement a cross-national study of managers. Journal of Cross-cultural Psychology, 21(2), 232–248.

Narayan, S., & Krosnick, J. A. (1996). Education moderates some response effects in attitude measurement. Public Opinion Quarterly, 60, 58–88.

Patton, J. H., Stanford, M. S., & Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. Journal of Clinical Psychology, 51(1), 768–774.

Paunonen, S. V., & Ashton, M. C. (2001). Big five factors and facets and the prediction of behavior. Journal of Personality and Social Psychology, 81(3), 524.

Pollock, L., Deaville, J., Gilman, A., & Willock, J. (2002). A preliminary study into stress in welsh farmers. Journal of Mental Health, 11(2), 213–221.

Rammstedt, B., & Farmer, R. F. (2013). The impact of acquiescence on the evaluation of personality structure. Psychological Assessment, 25, 1137–1145.

Rammstedt, B., Goldberg, L. R., & Borg, I. (2010). The measurement equivalence of big-five factor markers for persons with different levels of education. Journal of Research in Personality, 44, 53–61.

Rammstedt, B., & Kemper, C. J. (2011). Measurement equivalence of the big five: Shedding further light on potential causes of the educational bias. Journal of Research in Personality, 45, 121–125.

Roberts, B. W. (2009). back to the future: Personality and assessment and personality development. Journal of Research in Personality, 43(2), 137–145.

Roberts, B. W., Chernyshenko, O. S., Stark, S., & Goldberg, L. R. (2005). The structure of conscientiousness: An empirical investigation based on seven major personality questionnaires. Personnel Psychology, 58(1), 103–139.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. Psychological Monographs: General and Applied, 80(1), 1.

Sherlund, S. M., Barrett, C. B., & Adesina, A. A. (2002). Smallholder technical efficiency controlling for environmental production conditions. Journal of Development Economics, 69(1), 85–101.

Soto, C. J., John, O. P., Gosling, S. D., & Potter, J. (2008). The developmental psychometrics of big five self-reports: Acquiescence, factor structure, coherence, and differentiation from ages 10 to 20. Journal of Personality and Social Psychology, 94, 718–737.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society. Series B (methodological), 58, 267–288.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

Walker, L. S., & Walker, J. L. (1987). Stressors and symptoms predictive of distress in farmers. Family Relations, 36, 374–378.

Wuepper, D., & Lybbert, T. J. (2017). Perceived self-efficacy, poverty, and economic development. Annual Review of Resource Economics, 9, 383–404.