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The effect of cognitive function on the poor's economic performance: Evidence from Cambodian smallholder farmers

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Abstract

Despite manifold policy interventions, poverty still exists. Those most harshly affected are people living in rural areas of low-income countries. A seminal strand in the literature presents a promising avenue for analyzing the lives of the poor by suggesting that poverty impedes cognitive function. However, the real-world consequences of impeded cognitive function are yet to be discovered. We ask whether the level of cognitive function can help to explain the differences in economic performance of the poor. We conducted a field study in rural Cambodia using the well-established Raven's Progressive Matrix to elicit cognitive function. Employing stochastic frontier analysis, we find that the level of cognitive function of poor smallholder farmers helps in explaining differences in economic performance. Our findings suggest that impeded cognitive function results in a negative economic performance feedback loop, which can be a reason why some farmers appear to be stuck in poverty while others manage to escape it.

KEYWORDS
Cambodia, cognitive load, Raven's progressive matrix, smallholders, stochastic frontier analysis

JEL CLASSIFICATION
Q10, Q12, D91

1 | INTRODUCTION

Despite global efforts and substantial progress, around 10% of the global population still lives off less than 1.90 USD per day (World Bank, 2020). The vast majority of the global poor reside in rural areas and depend on agriculture as their primary source of livelihood (World Bank, 2018). Consequently, national and international policy often focus on smallholder farmer business development to combat poverty. In particular, programs and services aim to sustainably increase farm productivity to lift large shares of rural populations out of poverty (FAO, 2017). While substantial progress has been achieved during recent decades (World Bank, 2020), research suggests that interventions do not reach all individuals equally (Banerjee & Duflo, 2011). The reasons for this unequal impact of development interventions remain opaque. For example, although farmers often participate in training and extension services, many do not apply what they have learned. Similarly, farmers often receive inputs such as seeds or fertilizer, yet many do not use them (Cárdenas, 2016; Mullainathan & Shafir, 2013).

One explanation for persistent poverty suggests that the poor appear to engage in bounded rational behavior (Banerjee & Duflo, 2011), which causes them to drift increasingly deeper into hardship. Traditionally, poverty research has comprised two main strands: the first hypothesizes that the reasons for poverty are exogenous to an individual, such as a lack of access to markets or weather shocks; while the second postulates that an individual finds herself in poverty due to endogenous factors, for example, her subjective risk attitude (Bertrand et al., 2004). However, more recently a novel stream of literature has suggested that poverty creates its own unique mindset and behaviors (Mullainathan & Shafir, 2013; Shah et al., 2012).

Mullainathan and Shafir (2013) explain that a lack of financial means forces an individual to constantly manage limited resources, which creates a cognitive load that temporarily taxes the individual's cognitive function. One central feature of cognitive function is *fluid intelligence*, which describes the ability to think logically and solve problems in novel situations. Given that scarcity impedes cognitive function, an individual who is living in poverty can experience her fundamental cognitive capacity as being temporarily altered by her circumstances (Dean et al., 2019; Deck & Jahedi, 2015; Mullainathan & Shafir, 2013).

Schilbach et al. (2016) highlight an inherent paucity of evidence on the relationship between cognitive function and economic performance. Nonetheless, understanding this relationship is critical as resources invested, for example, in unwarily designed extension work for supporting the rural poor might prove to provide futile support for those with low cognitive function. Additionally, Dean et al. (2019) investigate potential poverty traps arising from impeded cognitive function. Understanding the link between cognitive function and real-world economic performance holds special interest as poverty may be both a cause and consequence of changes in cognitive function. Low cognitive function might lead to diminishing productivity and therefore potentially amplify poverty, creating a vicious feedback loop (Dean et al., 2019). Thus, it is pivotal—especially for policy-makers—to understand this link as it describes underlying mechanisms that could help to explain poverty and its persistence (Vohs, 2013). Above that, assessing real-world consequences can help in elaborating the magnitude of the newly-established link between poverty and impeded cognitive function for people experiencing financial scarcity.

While a limited but growing body of literature presents evidence of the direct path of how poverty impedes cognitive function (Dean et al., 2019; Haushofer & Fehr, 2014; Mani et al., 2013; Mullainathan & Shafir, 2013; Schilbach et al., 2016), the link between cognitive function and economic performance remains opaque, especially with respect to the lives of smallholder farmers (Dean et al., 2019; Schilbach et al., 2016). Previous work has mainly focused on income rather than productivity. For example, researchers have found a positive and statistically significant effect of cognitive function—measured through the Raven's Progressive Matrices (RPM)—on income in Colombia (Psacharopoulos & Velez, 1992), Mexico (Vogl, 2014) and Indonesia (Bargain & Zeidan, 2017)[1], and no statistically significant effect in Pakistan (Fafchamps & Quisumbing, 1999). Kaur et al. (2021) are the first to provide experimental evidence on the effect of financial scarcity on labor productivity in their study on manufacturing workers in India.

This article asks whether the level of cognitive function can help to explain differences in economic performance—measured as technical efficiency—of smallholder farmers. To answer our research question, we (i) measure the level of cognitive function of smallholder farmers, (ii) model the production process of farm output, and (iii) estimate their efficiency and the effect of cognitive function to explain differences in economic performance. Our methodological approach relies on stochastic frontier analysis (SFA). We model the production technology of smallholders in rural Cambodia and estimate their economic performance based on cognitive function, measured using the RPM test (Mani et al., 2013; Raven & Rust, 2008; Schilbach et al., 2016).

Our contribution to the literature is threefold. First, we measure cognitive function of poor smallholder farmers in Cambodia, which—to the best of our knowledge—no other study has done. As Dean et al. (2019) point out, "(…) an enhanced understanding of the psychological or cognitive lives of the poor is, in and of itself, of substantial value" (p. 59). Very little is known about cognitive function of the poor, while implications can be crucial. Generating a better understanding starts with collecting and reporting the level of cognitive function of the poor, as we do in this study. Second, we add cognitive function to the list of empirical drivers of technical efficiency. While the existing literature explains economic performance by addressing a host of socio-economic factors, psychological explanations for the differences in efficiency levels have rarely been considered (Manevska-Tasevska & Hansson, 2011; Nuthall, 2001). Third, we extend the link between poverty and cognitive function. While scholars suggest that financial scarcity reduces cognitive function, its consequences for economic performance have rarely been exam-

[1] Unlike all of the other aforementioned studies, Bargain and Zeidan (2017) do not use the RPM test. They also use a measure of fluid intelligence, but they utilize a broader *word recall* test.

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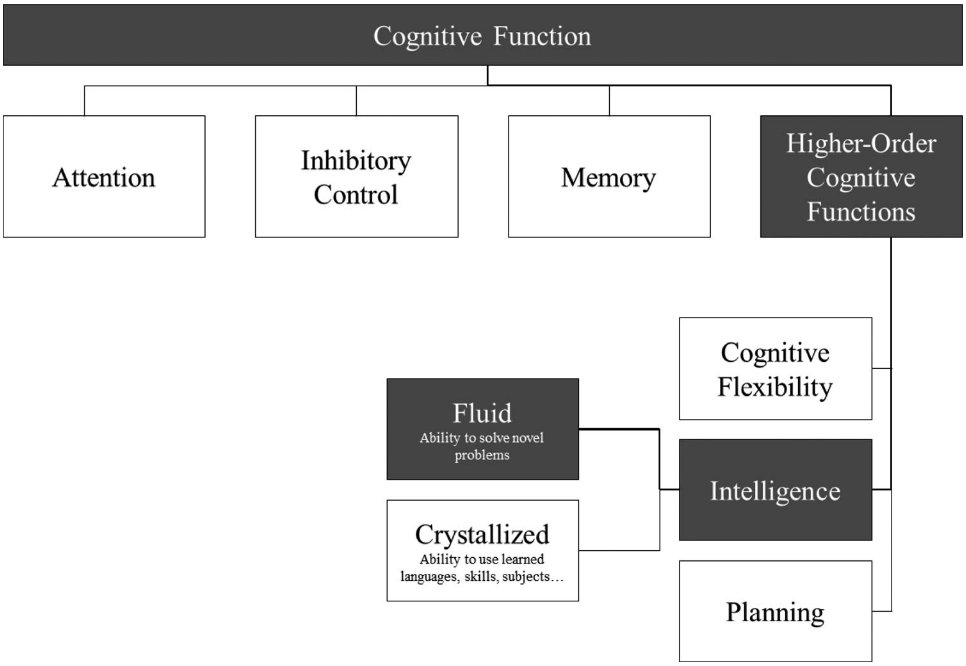

FIGURE 1 Overview cognitive function. Based on Dean et al. (2019), this study is focusing on the highlighted boxes

ined and in particular not among poor smallholder farm managers (Dean et al., 2019). In contrast to existing studies that focus on aggregate income (e.g., Vogl, 2014) or employ partial productivity measures (Kaur et al., 2021), we determine productivity in the framework of a production function and measure the effect of cognitive function on technical efficiency. This approach enables explicitly modeling how cognitive function relates to individual shortfalls in farm productivity under the explicit consideration of production technology.

The remainder of this article is organized as follows. In Section 2, we provide background information on the concept of cognitive function. In Section 3, we present the framework of our study, including the field setup, the study group and region, and the estimation approach. Section 4 presents the results from our SFA, followed by a discussion of our findings in Section 5. Finally, we end with some concluding remarks in Section 6.

2 | POVERTY, COGNITIVE FUNCTION, AND ECONOMIC PERFORMANCE

Cognitive function is broadly defined by Dean et al. (2019) as "mental processes that control one's attention, dictate one's ability to work with information, and are required for deliberate activity" (p. 60). Figure 1 illustrates a simplified overview of broadly-agreed-upon elements of cognitive function. The main categories of cognitive function include attention, inhibitory control, memory and higher-order cognitive functions, where the latter includes multiple basic cognitive functions.

In our study, we measure fluid intelligence, which is one component of an individual's intelligence. Crystallized intelligence builds on previously-acquired knowledge, whereas fluid intelligence refers to an individual's ability to handle novel situations (Dean et al., 2019; Horn & Cattell, 1966).

We focus on fluid intelligence due to two main reasons. First, adapting to novel situations is a highly important ability for small farm managers and thus a crucial variable when studying differences in economic performance. Farm managers need to operate a wide variety of tasks throughout the production cycle, that is, from seeding to harvesting and along the supply chain, including, for example, understanding demand (deciding on their product portfolio for the given season), finding suitable business partners and selling at the appropriate time and place While behavioral factors appear to be of high importance when it comes to making these decisions (Knapp et al., 2021), another interesting dimension exists, especially in the lives of smallholder farmers. Farm managers need to constantly adapt to previously-unknown circumstances in the market and find solutions for a wide range of novel problems (Schilbach et al., 2016), which demands fluid intelligence. Second, ultimately we aim to contribute to better understand the potential relevance of cognitive load, that is, the temporary impairment of (especially) fluid intelligence (Mani et al., 2013; Mullainathan & Shafir, 2013; Schilbach et al., 2016).

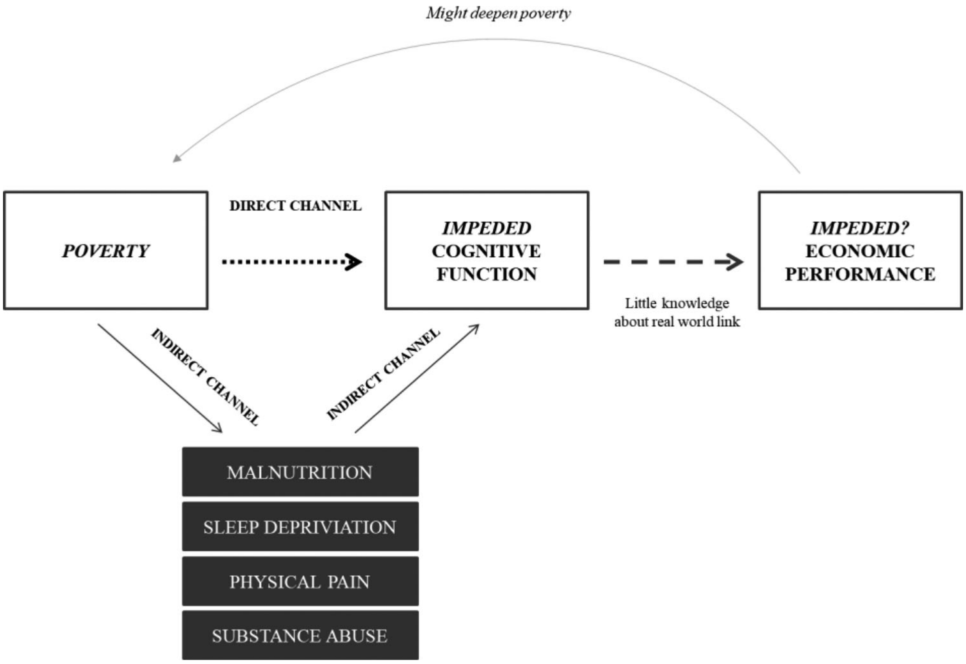

FIGURE 2 Pattern of potential poverty trap. Based on Dean et al. (2019)

As seen in Figure 2, there are two relevant links that are studied rather independently: first, the link between poverty and cognitive function (spotted arrow), and second (dashed arrow) the link between cognitive function and real-world implications (in our case, economic performance). The fore interaction (spotted arrow in Figure 2) is studied by Mani et al. (2013). Relying on both laboratory and field studies, Mani et al. (2013) conclude that poverty critically reduces cognitive function. As farmers suffer from cognitive load during times of financial scarcity, their entrepreneurial decisions might fall short accordingly. The basic idea tested in the study is that scarcity of financial resources creates cognitive load as the individual starts to mentally tunnel on her financial burden. In other words, while an individual can possess a certain level of cognitive function, this level can be altered by the circumstance of poverty, that is, scarcity of essential financial means. An individual experiencing scarcity will tend to tunnel on her scarcity problem, that is, experience cognitive load, which will leave less cognitive function for other tasks. Once the financial problem disappears, the individual's cognitive load also disappears and she returns back to her normal level of cognitive function.

Further empirical studies aiming to understand the fore link in Figure 2 either confirm (Ong et al., 2019) or reject or only partly confirm (Carvalho et al., 2016; Dalton et al., 2020; Fehr et al., 2019) the findings of Mani et al. (2013). For further reading, see de Bruijn and Antonides (2021), who provide an up-to-date overview of the overall evidence of the scarcity theory. Ong et al. (2019) investigate the effect of debt relief on the psychological lives of low-income subjects in Singapore. They do not measure fluid intelligence but inhibitory control, which is a different aspect of cognitive function (also shown in Figure 1). When comparing participants' before and after debt relief, the authors find improved inhibitory control after debt relief. Thus, the results of Ong et al. (2019) point in a similar direction as those of Mani et al. (2020), indicating that poverty (i.e., financial scarcity) impedes cognitive function. Carvalho et al. (2016) assess the effect of financial changes around payday for low-income US households. They capture a battery of behavioral and financial variables such as risk attitude, inter-temporal preferences, and cognitive function to explore how financial fluctuation affects these different dimensions. While the authors mainly measure inhibitory control to assess cognitive function, they show that the results strongly correlate with results from the fluid intelligence test (conducted with a part of the sample). When assessing the cognitive test scores before and after payday for the overall sample, the authors do not find meaningful differences, and thus they cannot confirm the findings of Mani et al. (2013). However, Mani et al. (2020) revisit the findings from Carvalho et al. (2016) and suggest that weaknesses in the control design of the experiment could explain these results. Dalton et al. (2020) and Fehr et al. (2019) both include the RPM test for fluid intelligence in their analysis of Vietnamese microentrepreneurs and Zambian smallholder farmers, respectively. Dalton et al. (2020) investigate the effect of financial worries, induced by a hypothetical scenario of damage to a valuable asset for the participant, on risk attitude and other variables, finding no effect of financial worries on cognitive function. Fehr et al. (2019) replicate the Mani et al. (2013) study, investigating smallholder farmers in a pre-/post-harvest comparison. When only considering the results from the RPM test (in their pre-post comparison), Fehr et al. (2019) can confirm the findings of Mani et al. (2013) as participants score better after harvest. However, when looking at their comprehensive analysis of cognitive function, they report an inconsistent relationship between financial scarcity and cognitive function.

Finally, there are also indirect ways in which poverty can potentially impede cognitive function (as also depicted in Figure 2). For example, as an individual is poor, she is less able to buy sufficient food and thus might suffer from undernourishment. In turn, undernourishment can then temporarily (for the time of the nutrient shortage) lower the cognitive function of an adult individual (Dean et al., 2019).

Regarding the latter link (dashed arrow of Figure 2), limited evidence suggests that the level of cognitive function can have real-world consequences for economic performance (Bargain & Zeidan, 2017; Fafchamps & Quisumbing, 1999; Psacharopoulos & Velez, 1992; Vogl, 2014). Kaur et al. (2021) are the first to explore the effect of financial scarcity on productivity in a field experiment with production workers in rural India. In other words, they consider the entire chain in Figure 2 (spotted and dashed arrow). By constantly measuring attention and productivity of output while varying the payday among the different treatment groups, the authors present evidence that improved cognition (caused by the alleviation of financial scarcity) may have a direct effect on productivity. While Kaur et al. (2021) study the economic consequences of production workers, the link between cognitive function and economic consequences with respect to smallholder farm managers is unknown.

In our study, we focus on the latter part (dashed arrow) of the chain in Figure 2. Regardless of the reason for the level of cognitive function, we set out to understand how cognitive function relates to real-world economic output.

3 | MATERIALS AND METHODS

3.1 | Study region and sample

We study smallholder farmers from northeastern Cambodia. With a gross national income per capita of 1075 USD, Cambodia is clustered as a least developed country (United Nations, 2018). Despite experiencing economic growth over recent years, Cambodia is nevertheless among the poorest countries in the region and thus a highly appropriate area in which to conduct our study (World Bank, 2020). Moreover, the country presents itself as a suitable area to study the life of smallholder farmers as approximately 82% of Cambodians are farmers, and most of them are rural smallholder farmers (Sotha, 2019), with each household having less than 2 ha (Sotha, 2019). Within Cambodia, we selected the poorest province—Ratanakiri (Asian Development Bank, 2014)—to undertake our data collection. Ratanakiri is a rural upland province bordering Lao PDR and Vietnam, whose over 150,000 citizens are predominantly indigenous people. Most of the residents of Ratanakiri depend on agriculture as their source of living (Sisovanna, 2013). Rice is mainly cultivated for household consumption, while cassava, cashew and rubber are the main cash crops (Ritzema et al., 2019). Up to the 1990s, the region was mostly cultivated collectively by the indigenous people who practiced slash-and-burn techniques. Only recently have the farmers in Ratanakiri cultivated cash crops, with a special focus on cassava. This development was partly fueled by growing demand for livestock products in China and Vietnam, which has led to rapidly increasing imports of feed cassava from Cambodia. Due to the high demand, cassava is a key source of cash for the people of Ratanakiri (Gironde & Peeters, 2015; Joshi, 2020).

Our sample contains 227 smallholder farmers and spreads over 16 villages in the province of Ratanakiri. Given the absence of household lists in the region, the randomization routine relied on local expert knowledge to generate a cross-sectional sample of the respective villages. Local enumerators privately guided the participants throughout the research session, which comprised a test part and a questionnaire part. After a 3-h session, the participants received a payout equivalent to one day's wage.

Table 1 depicts the basic characteristics of our sample and Figure 3 shows correlations of the variables employed. Regarding crop production, the farm portfolio is homogeneous among the farmers as the majority of them predominantly cultivate rice and cassava. The farms in our sample produce rice for both self-consumption and sale. Additionally, the participants cultivate a negligible amount of other crops such as vegetables, pulses, beans and fruits. Fewer than 1% of our sample cultivate rubber on their land. The only other dominant cultivation is cashew trees. However, we are unable to model cashew production as the farmers often could not recall the time of plantation. As cashew trees need to grow for a few years before they reach maturity and produce fruits, we could not unambiguously determine whether the reason for a specifically high/low amount of output is due to the age of the tree or the technology used by the farmer.

Therefore, our revenue variable relies on the revenues generated from total cassava and rice output. For self-

TABLE 1 Descriptive statistics ($n = 227$)

Statistic	Unit	Mean	St. Dev.	Min	Pctl (25)	Pctl (75)	Max
Revenue	USD	1306.20	1440.50	16.31	420.88	1712.50	11,250.00
Land size	ha	2.47	1.80	.10	1.00	3.00	.00
Labor cost	USD	1009.91	1140.09	8.00	322.00	1248.00	7344.00
Materials	USD	60.29	111.36	.00	.10	75.00	1055.00
Soil quality	Ordinal†	2.49	.77	1	2	3	4
Age	Years	38.60	14.21	13	28	49	75
Education	Years	2.92	3.09	0	0	5	12
Ravens	Ordinal‡	6.07	2.48	0	4	8	11
Yield	USD ha^{-1}	533.83	361.31	10.87	267.69	720.88	1902.30

†Likert scale ranging from 1 to 5, with 1 being very good and 5 being very bad.
‡Measured as the number of correct answers given in the RPM ranging from 0 to 12.

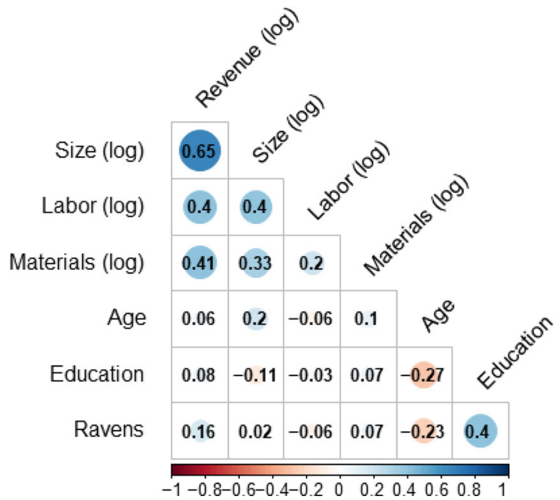

FIGURE 3 Correlation matrix of the variables employed in the analysis [Color figure can be viewed at wileyonlinelibrary.com]

consumed output we calculate revenue using the average received price in the sample to approximate the market price. We observe substantial variation in annual crop revenues ranging from 16 USD to 11,250 USD as well as farmland, which ranges from .10 to 10 ha. Materials measures the expenses for seed purchases and agrochemicals and labor pools family labor and hired labor, and we express total labor as the sum of labor expense and opportunity cost per farm, using average wages in the sample. Soil quality is rated as good to satisfactory on average. All input and output quantities refer to the period of one marketing year. Regarding to socio-economic characteristics, on average farmers are 39 years of age and have received three years of formal education.

3.2 | Measurement of cognitive function

We conducted the RPM test with 227 smallholder farmers in rural Cambodia. To test for cognitive capacity, the participants performed the commonly-used article-based RPM test (Schilbach et al., 2016). The RPM test involves a sequence of shapes with one shape missing. Participants must choose which of several alternatives best fits in the missing space. Like Mani et al. (2013) and as proposed by Dean et al. (2019), we also used a compressed version of the RPM test. In its raw version, the test comprises 60 puzzles. After conducting a pilot with smallholder farmers in the region, we decided on 12 puzzles with ascending difficulty to use in the field study.[2]

Every participant was presented with the same preselected matrices of the standard RPM test. The RPM was always the first element of the research session. There was no time pressure for the RPM test and the enumerators were intensely trained on how to present the test to ensure standard procedure in the field. Participants received two practice trials, and they were only allowed to start the actual test after correctly solving both. Raven's test is a widely-used and universally-accepted tool to measure fluid intelligence. It is independent of acquired knowledge and non-verbal, that is, it is suitable for illiterate test takers (Dean et al., 2019; Mullainathan & Shafir, 2013; Raven, 1938; Raven & Rust, 2008). As part of our study design, we visited the participants between August and October 2018, during the time of the year when farmers have the least income (see Figure A1 in the Appendix). Thus, we captured the moment of highest financial scarcity for the local population, and thereby likely the moment of heaviest cognitive load (Mani et al., 2013).

[2] 2013 Mani et al. (1977) also use this procedure to select their short RPM test. Our enumerators as well as the entire staff took the short RPM test and they were all able to answer all twelve puzzles correctly. Note that the RPM puzzles are kept under tight wraps and protected by copyright to not be printed elsewhere, as the puzzles are used for psychological tests. Therefore, we are unable to present the chosen puzzles.

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3.3 | Stochastic production frontier and technical efficiency

Dating back to the seminal works of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), stochastic frontiers have been widely applied to measure productivity in a variety of production scenarios. Within these frameworks, a diverse set of approaches has been developed that implement measurement of technical efficiency (O'Donnell, 2018; Parmeter & Kumbhakar, 2014). Also in the context of agriculture in developing countries, SFA has found extensive application to measure farm performance and pinpoint determinants of farm efficiency (e.g., Baffoe-Bonnie & Kostandini, 2019; Bravo-Ureta et al., 2020; Jimi et al., 2019; Mishra et al., 2018; Rao et al., 2012; Sherlund et al., 2002; Wollni & Brümmer, 2012). The critical advantage of these approaches compared—for instance—with yield models is that they enable distinguishing between the given technology—which determines some level of productivity that is exogenous to the producer in the short term—and technical efficiency, which measures the individual performance of producers in managing their resources and technology. First introduced by Farrell (1957), technical efficiency can be viewed as the ratio between individually-achieved output and maximum attainable output, that is,

$$TE_i = \frac{y_i}{y_i^*} \tag{1}$$

at a given technology. Here, y_i is the output achieved by one producer and $y^*{}_i$ is the best-practice output, which in turn is conditioned by the technology.[3] In other words, technical efficiency is a measure of performance that benchmarks an individual's performance with the best-practice scenario.

The technology and best-practice scenario can be determined empirically using production frontiers where productive inputs predict the output level. We rely on the cross-sectional version of an error component models first introduced by Battese and Coelli (1995), which describes the stochastic frontier model as:

$$\ln(v_i) = \ln F(x_i, \beta) - u_i + v_i \tag{2}$$

where x_i are inputs used in the production process and β is a vector of associated technological parameters (Parmeter & Kumbhakar, 2014), which define the output y_i of farms. Output is measured as revenue from rice and cassava production, and inputs are land, labor and materials, which comprise expenditures for seed and agrochemicals. As y expresses revenues from crop production, Equation (2) may be referred to as a revenue function. The error components u_i and v_i denote technical efficiency and statistical noise, respectively. Thus, we assume that the productivity of the smallholder producers is determined by a homogeneous technology, individual shortfalls in efficiency of production as well as some stochastic noise.

This approach is particularly sensitive to the assumptions imposed on the distribution of the inefficiency term as well as the functional form. We assume the asymmetric distribution of the inefficiency term $u_i \sim N^+(0, \sigma^2_{u_i})$ and model $\sigma^2_{u_i} = \exp(z_j{}'\gamma)$ where $\boldsymbol{z}_i$ are potential determinants of inefficiency (Wang, 2002). The individual efficiency scores can be retrieved as $TE_i = exp(-u_i)$ and indicate the proportion of potential output that is actually achieved by farmer i. While the half-normal distribution of our framework is commonly used in SFA applications, Parmeter and Kumbhakar (2014) discuss a variety of alternative distributions that have emerged in the literature. In Appendix B.2, we apply and discuss several alternative distributional assumptions to test the robustness of our results.

Regarding the production technology, we impose a Cobb–Douglas-type functional form of $lnF(x_i,\beta)$, which is a superior choice compared with a translog functional form, suggested by a likelihood-ratio test[4]. Finally, we assume the symmetric error term $v^i - N(0, \sigma^2_v)\ v$. We estimate the stochastic frontier by means of maximum likelihood (ML).

4 | RESULTS

Figure 4 depicts the correct answers in the RPM test. As previously mentioned, the puzzles are arranged by difficulty, with the first puzzle being the easiest and the 12th puzzle being the most difficult. The order was chosen based on a pilot study with smallholder farmers from the region. Three out of 227 participants were unable to answer any puzzle correctly (0) and no participant was able to answer all 12 puzzles correctly (12). We see that most often the participants managed to answer the first five, six, seven, or eight puzzles correctly. On average, the participants answered six out of 12 puzzles correctly. This is comparable with the sample of Indian farmers from Mani et al. (2013), where Indian farmers score 5.45 out of eight correct items post-harvest and 4.35 out of eight correct items pre-harvest.

Table 2 depicts the resulting coefficients and associated standard errors of the production function and the

[3] Vice versa, from an input perspective, technical efficiency is the ratio between individually-used inputs and the minimum level of input use.

[4] The translog production model is provided in Appendix B.1.

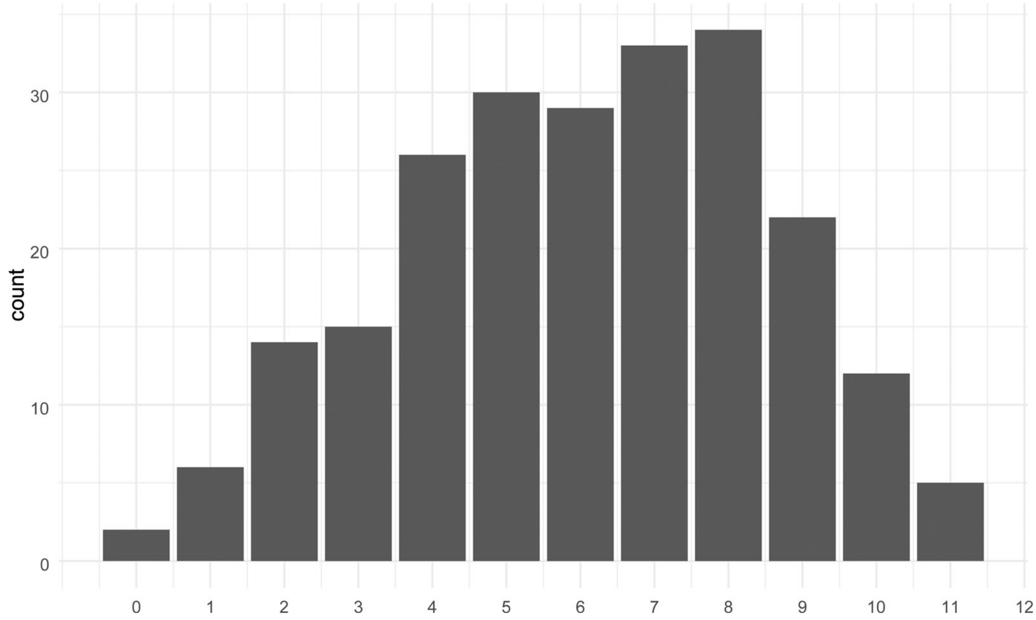

FIGURE 4 Correct answers in the RPM test ($N = 227$)

TABLE 2 Revenue functions and determinants of inefficiency parameter estimates

	(1)	(2)
Technology		
(Intercept)	64*** (.09)	.62*** (.09)
Land size	.83*** (.07)	.82*** (.07)
labor cost	.08** (.04)	.09** (.04)
Materials	.06*** (.01)	.06*** (.01)
Soil quality	−.19 (.13)	−.18 (.13)
Inefficiency		
(Intercept)	1.14 (1.06)	1.93* (1.13)
Age	−.06 (.05)	−.07 (.05)
Age^2	.00 (.00)	.00 (.00)
Education	−.16*** (.05)	−.13** (.05)
Ravens		−.11** (.05)
σ	.41*** (.06)	.42*** (.06)
Mean TE	.55	.56
Log likelihood	−237.46	−235.19
Observations	227	227

***$p < .01$; **$p < .05$; *$p < .1$.

determinants of inefficiency.[5] Since the variables have been standardized by their means, the coefficients can be interpreted as elasticities at the sample mean. The technology components of the Cobb–Douglas production function show signs and magnitude as expected. The sum of productive input elasticities is .97, indicating almost constant returns to scale. For soil quality, we find no statistically significant effect. One possible explanation for this finding is that soil quality is rather homogeneous among the farm households. IFAD (2017) hint towards homogeneous soil structures, as they find overall low soil quality on smallholder farms in northeastern Cambodia.

The average inefficiency levels are 55% and 56% of maximum possible output. Thus, we observe considerable inefficiency levels on average among the farmers. In turn, this means that the farms in our sample can potentially produce on average 44%–45% more output at the given set of input use and technology. This is lower than the findings of Kea et al. (2016), who analyze the technical efficiency of rice producers in Cambodia and find a national average technical efficiency of 78.4%. However, the average technical efficiency of rice farmers for the mountain region—which includes Ratanakiri—was 53% in 2015. Our model also confirms the findings of Nguyen et al. (2018), who estimate an average farm efficiency of 60% among Cambodian farmers in the Stung Treng province (a province neighboring Ratanakiri province), including crops such as rice, cassava, corn, and nuts in their SFA.

[5] The stochastic frontiers have been estimated using the R packages "npsf" Badunenko et al. (2020) and "sfaR" (Dakpo et al., 2021).

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TABLE 3 Mean marginal effects of determinants of inefficiency

	(1)	(2)
Age	−.022	−.025
Age^2	.000	.000
Education	−.060	−.049
Ravens		−.042

As potential drivers of inefficiency, we include cognitive function (*Ravens*), age, and education as z variables in our model. Cognitive function is a statistically significant explanatory factor and robust when controlling for effects of age and education. There is no statistically significant age effect. However, education also appears to be a statistically significant explanatory factor. The magnitude of the effect of education slightly diminishes in the model that considers cognitive function.

Table 3 illustrates the marginal effects as derived from the inefficiency model parameters. If an individual scores one unit higher in the RPM test, her inefficiency decreases by 4.2 percentage points. Likewise, one year of education reduces inefficiency by 4.9% in the fully specified model.

The results from the SFA are critically dependent on the assumption of the half-normally distributed inefficiency as well as the choice of the Cobb–Douglas functional form in the production function. In Appendix B.1, we provide a discussion and application of the alternative specification of a flexible translog functional form, albeit which may be rejected in terms of likelihood ratios. In Appendix B, we challenge the assumption of half-normally distributed inefficiency and impose three common alternative distributional assumptions on the main model. The coefficients in the production frontier and the effects of the determinants of inefficiency—including our main variable of interest RPM—remain robust across these different specifications.

5 | DISCUSSION

Our analysis targets the key question of how cognitive function affects economic outcomes, which has been raised in the relevant literature (Dean et al., 2019; Kremer et al., 2019; Schilbach et al., 2016). We target at contributing to this open question with our analysis. Our results show that higher cognitive function translates into higher efficiency levels. Furthermore, with respect to the marginal effect of RPM, revisiting the results from Mani et al. (2013) can aid in placing our findings—and thus the economic outcome of cognitive function—in perspective. The authors find that farmers score on average 4.35 correct items prior to harvest and 5.45 correct items post-harvest. When considering our estimates, this might serve as an orientation for interpreting our effect. Moving within their own natural financial fluctuations, the Indian farmers increased their RPM test performance by over one unit (on average). Assuming the same for our sample would mean that natural fluctuations of cognitive function result in a 4.2% output increase on average. Our results suggest that cognitive function has a reasonable effect on economic performance and thus should be taken into account by policy-makers when aiming to support smallholders.

Before discussing the implications of our findings on the relationship between productivity and cognitive function, we note that the level of cognitive function appears to be generally low among the surveyed farmers. None of the participants within our sample was able to answer all 12 puzzles of the RPM test, and on average we see a score of six out of 12 correct puzzles. Regardless of why the test scores are so low—due to either cognitive load or other reasons—the results indicate that considering cognitive function holds importance when designing both empirical studies and policy instruments. Moreover, further research in Cambodia and among smallholder farms in general is needed to better contrast such results and establish the basic mechanisms and consequences of the cognitive situation of smallholder farmers.

Within our analysis we cannot distinguish whether cognitive function is mainly driven by cognitive load or other factors. However, while we generally assume that cognitive load drives a significant portion of cognitive function based on empirical results from the literature (e.g., Dean et al., 2019; Fehr et al., 2019; Kremer et al., 2019; Mani et al., 2013; Mullainathan & Shafir, 2013; Ong et al., 2019; Schilbach et al., 2016), the particularly low performance in the RPM tests supports the hypothesis of strong cognitive load effects, given that the data were collected at times of highest scarcity. Thus, if the first link of Figure 2 exists, our findings provide evidence for a downstream mechanism: if poverty impedes cognitive function (as suggested by literature) and impeded cognitive function translates into inferior economic performance (as suggested through our findings), then this mechanism can deepen poverty and our findings serve as an indicator for a potential poverty trap that is related to cognitive function. Under such circumstances, two aspects worthwhile mentioning emerge: (1) with respect to our analysis, the empirical relationship is subject to endogeneity and should only be interpreted in context of poverty traps and feedback loops; and (2) with respect the interpretation of our findings, alleviating the financial burden can alleviate cognitive load. Policy-makers could thus focus on providing financial resources to the poor and/or assist to secure and accumulate cash, for example, by supporting savings groups. One prominent policy tool for this case is the unconditional cash transfer.

Haushofer and Shapiro (2016) show positive effects of unconditional cash transfers in Kenya, including because they increase mental well-being.

An opposing hypothetical scenario is that cognitive load (caused by poverty) is not at play and the level of cognitive function is influenced other idiosyncratic characteristics. In this case, the fore link of Figure 2 does not hold, as indicated by, for example, Carvalho et al. (2016) and Dalton et al. (2020). This means that the level of cognitive function is independent of financial fluctuations. Therefore, policy interventions aiming at combating poverty among smallholders could be more successful in focusing on providing nuanced interventions that incorporate defaults and other useful features. For instance, the work done by Duflo et al. (2011) can serve as an example. The authors nudge farmers to use fertilizers by designing the delivery as a default as opposed to on-demand purchases, with positive effects on fertilizer use. Furthermore, the study by Dzanku et al. (2021) serves as another interesting example. The authors show that sending mobile phone voice message reminders to smallholder farmers can support in recalling knowledge when actually needed.

However, regardless of the specific root causes of the level of cognitive function, differences in cognitive function help to explain shortfalls in economic performance, especially when it comes to managing the farm business. For instance, if the level of cognitive function is low, an individual might be less able to be attentive at long school days or during extension sessions. Thus, policies can increase the size and frequency of educational infrastructure for the rural population, and if the level of cognitive function is not accounted for, they are potentially redundant for the most vulnerable. Cognitive function therefore presents itself as a new, previously-omitted determinant of technical efficiency.

6 | SUMMARY AND CONCLUDING REMARKS

We have analyzed the effect of cognitive function on economic performance of 227 smallholder farmers in rural Cambodia. For this purpose, we used the RPM test to measure cognitive function, and collected data on sociodemographic and farm production characteristics. In synthesis, our field study reveals that (i) farm managers scored particularly low in the RPM test on average, indicating the presence of cognitive load. Moreover, (ii) average efficiency is also low, ranging between 55% and 56% of technically achievable output. Finally, (iii) economic performance is associated with cognitive function. If a participant scores one unit higher in the RPM test, her inefficiency decreases on average 4 percentage points. Altogether, we extend the literature by providing empirical evidence on the consequences of impaired cognitive function among smallholder farmers in rural Cambodia.

More generally, our results emphasize that the level of cognitive function impacts economic performance. Many of the policy interventions to combat poverty focus on factors that are exogenous to individuals, such as education, infrastructure and technology. However, our study suggests that such measures could partly be off-target if vulnerable individuals are experiencing impeded cognitive function. Furthermore, when incorporating the possibility of cognitive load caused by financial scarcity as a reason for impeded cognitive function, our results suggest that cognitive impairment can be a reason why some farmers appear to be stuck in poverty while others manage to escape it. Nonetheless, if cognitive function is not accounted for when designing interventions for smallholder farmers, those most mentally burdened might be left behind. We suggest accounting for low cognitive power by providing unconditional cash transfers or safety nets such as insurance for the poor to fall back on and including defaults such as regular input deliveries to avoid further taxing the limited cognitive resources of the poor. By carefully designing policy implications to meet the need of those with low cognitive function, small farm managers will gain opportunity to engage in new business avenues rather than being excluded from even making such a choice.

Future studies could focus on eliciting cognitive function of smallholder farmers to shed light on the cognitive situation. Furthermore, this study could be replicated in other countries to move from empirical evidence from rural Cambodia to broader evidence of the link between cognitive function and economic performance. Moreover, future work could focus on other correlates of poverty to elicit the potential existence of cognitive load.

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SUPPORTING INFORMATION

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APPENDIX A

A: Cash flow

B: Stochastic production frontiers with alternative assumptions on functional form and distribution of inefficiency

B.1: Translog production function In this section, we compare the Cobb–Douglas specification of our main model with a the commonly used translog specification of the production function which takes the form of3and thereby extends the Cobb–Douglas production function by introducing cross-terms and squared terms of the productive inputs. We still include soil quality as a shifter in the model and the specification of inefficiency is equivalent to that of the main model. Table B1 juxtaposes the main Cobb–Douglas model (1) and the translog model

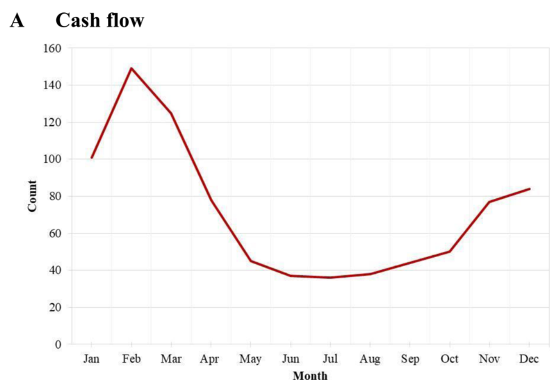

FIGURE A1 Cash flow over a year. This Figure presents an analysis of participants' annual cash flow pattern. The participants were asked the following question: 'Over the year, could you indicate when cash flows in?' The enumerator could then mark all months in which the participant stated to receive some form of income. This figure depicts the total number of households that received income (count) on the vertical axes and the months of a year on the horizontal axes. It shows that most households receive cash around February, while the households are relatively income scarce between May and October [Color figure can be viewed at wileyonlinelibrary.com]

TABLE B1 Cobb–Douglas (1) versus translog (2) specification of functional form

	(1)	(2)
Technology		
(Intercept)	.62***	.61***
	(.09)	(.10)
Land size	.82***	.88***
	(.07)	(.09)
Labor cost	.09**	.08
	(.04)	(.06)
Materials	.06***	.07
	(.01)	(.05)
Soil quality	−.18	−.13
	(.13)	(.13)
Size × labor cost		.11 (.08)
Size × materials		.01 (.03)
Labor cost × materials		−.03* (.02)
Size^2		−.08 (.15)
Labor^2		−.01 (.04)
Materials^2		.01 (.02)
Inefficiency		
(Intercept)	1.93* (1.13)	1.96* (1.16)
Age	−.07 (.05)	−.07 (.05)
Age^2	.00 (.00)	.00 (.00)
Education	−.13** (.05)	−.14** (.05)
Ravens	−.11** (.05)	−.11** (.05)
Log likelihood	−235.19	−232.92
Meant TE	.55	.56
Observations	227	227

***$p < .01$; **$p < .05$; *$p < .1$.

(2). While Education and Ravens are robust to this alternative functional form, modeling the additional parameters of the translog form does not yield an improved model. The p-value of the likelihood ratio test is .59 at six degrees of freedom and thus strongly favoring the Cobb–Douglas specification at all conventional significance levels.

TABLE B2 Models with alternative assumptions on the distribution of inefficiency

	(1)	(2)	(3)	(4)
Technology				
(Intercept)	.62***	.39***	.61***	.43***
	(.09)	(.09)	(.11)	(.12)
Land size	.82***	.81***	.81***	.81***
	(.07)	(.07)	(.07)	(.07)
Labor cost	.09**	.10**	.10**	.10**
	(.04)	(.04)	(.04)	(.04)
Materials	.06***	.07***	.06***	.06***
	(.01)	(.01)	(.01)	(.01)
Soil quality	−.18	−.16	−.16	−.16
	(.13)	(.13)	(.13)	(.13)
Inefficiency				
(Intercept)	1.93*	1.06	.39	.85
	(1.13)	(1.84)	(1.25)	(1.68)
Age	−.07	−.07	−.05	−.07
	(.05)	(.08)	(.06)	(.07)
Age^2	.00	.00	.00	.00
	(.00)	(.00)	(.00)	(.00)
Education	−.13**	−.20**	−.12**	−.18**
	(.05)	(.10)	(.06)	(.09)
Ravens	−.11**	−.16*	−.12**	−.15*
	(.05)	(.08)	(.06)	(.08)
λ				.37
				(.85)
Mean TE	.56	.68	.56	.63
Observations	227	227	227	227

***$p < .01$; **$p < .05$; *$p < .1$.

B.2: Alternative distributional assumptions of inefficiency

In this section, we test the results of the main models against alternative distributional assumptions of the one-sided error term that captures the inefficiency. The results are depicted in Table B2. Our baseline model (column (1)), inefficiency is assumed to follow a half-normal distribution. Models (2)–(4) employ a common alternative assumption of an exponential distribution (2), a generalized exponential distribution (3) (Papadopoulos, 2021) as well as a truncated skewed Laplace distribution (4) (Wang, 2012) of inefficiency, respectively. We observe only minor changes in both coefficients and their precision where in particular both parameters for Ravens and Education are consistently estimated across the different models. We thus find the results of the baseline model to be robust against different assumptions of inefficiency.