Technology Gaps Drive Inequality in Production for Farmers with Disabilities

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Abstract

In sub-Saharan Africa, agriculture is vital, yet the exclusion of disabled individuals from farming hinders sustainable development and fairness. This study examines crop production in Ghana, focusing on the disparities in technology usage and crop production efficiency between farmers with and without disability. Using meta-stochastic frontier analysis and matching techniques on farm-level data for 2012/13 and 2016/17, surveys we found negligible technical efficiency differences (<0.5%) between the groups. However, the productive capacity of disabled farmers technology is 13 percentage points lower than their non-disabled counterparts, resulting in a 13% production disadvantage. This gap is linked to limited per hectare use of planting materials, labor, fertilizer, and agro-chemicals. The technology gap highlights significant inequality, underscoring the need for interventions to enhance inclusivity and productivity for disabled individuals. Addressing this issue is vital for equitable agricultural development and economic growth.

Keywords: disability parity; agricultural technology; technical efficiency; Ghana; production gap

JEL Classification: J14, Q12, O13, O33, I38

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1. Introduction

The World Bank estimates that approximately one billion individuals globally suffer from disability, constituting about 15% of the world's population. A significant majority, around 80% of these individuals reside in low- and lower-middle-income countries [1]. Disabilities can vary widely; they may be visible or invisible and may encompass physical, cognitive, or sensory impairments. These individuals often encounter numerous challenges in their daily lives, stemming from their diverse conditions. Extensive research reveals that these challenges intensify issues for persons with disabilities (PWDs) and their households, leading to pronounced disparities in food insecurity [2], [3], pervasive poverty [4], [5], [6], [7], [8], restricted access to the labor market [9], inadequate housing [10], [11], and limited healthcare services [12], [13]. Recognizing the urgent need to bridge these gaps, the United Nations calls on countries around the world to bolster economic opportunities for all, in line with its ambitious objectives to eradicate poverty and hunger while leaving no one behind as integral components of the Sustainable Development Goals (SDGs) [14]. Achieving these objectives, however, depends significantly on evidence-based research to pinpoint and mitigate disparities across diverse economic and social demographics.

In sub-Saharan Africa (SSA), a region where agriculture is the cornerstone of the economy, PWDs are often excluded from farming opportunities [15]—which is a critical issue given agriculture's role in employment, economic growth, and food security. Ensuring equitable access of PWDs to agricultural opportunities is essential for fostering sustainable development and social justice. Yet, the relationship between disability and agricultural productivity, especially in terms of technology adoption and its optimal use, generally remains underexplored. This neglect not only sidelines a significant segment of the disabled community but also fails to recognize their potential to significantly contribute to the agricultural sector and, by extension, the wider economy.

Ghana provides a backdrop for exploring the relationship between disability and agricultural productivity. As a middle-income nation that has witnessed substantial GDP growth, Ghana's economy is nonetheless characterized by a significant proportion of its population—between 7-10%—living with disabilities [16]. Many of these individuals are older, females, and reside in rural areas, where agriculture forms the economic bedrock [17]. Despite this demographic's potential to contribute meaningfully to agricultural production, PWDs in Ghana face systemic challenges, including discrimination, unemployment, and broader societal hardships [3], [16], [18], [19]. The role of agriculture as a viable pathway for generating sustainable economic opportunities for PWDs has been underexplored, particularly given the sector's labor-intensive nature and the unique challenges and contributions of disabled individuals. Historically, PWDs have been marginalized and faced discrimination across various societal dimensions [16]. This systemic overlook raises a critical yet largely unexplored question: Does this societal backdrop contribute to a discernible disparity in technology adoption and production efficiency, and by extension, agricultural productivity growth for PWDs in Ghana? This question underscores the necessity of examining the agricultural sector not only as a source of livelihood but also as a potential platform for fostering inclusivity and economic empowerment for PWDs.

Our research delves into the nuances of disability parity within Ghana's agricultural sector, with a focus on: (1) assessing the degree of disparity in technology level and technical efficiency of crop production among farmers, considering the disability status of the farmer, their immediate family, or household members; and (2) examining variations in this disparity across different demographic and agricultural contexts, including gender, age, education level, crop type, and geographical location. To conduct our analysis, we employ a meta-stochastic frontier framework with a specific focus on disability. This approach is applied to data gathered from two cross-sectional population-based surveys conducted in Ghana, encapsulating 19,862 farmers in 2012/13 and 2016/17 across all commercially cultivated crops amongst others. This dataset, which is nationally representative, offers a rare opportunity to empirically examine how agricultural production factors (such as elasticities, returns to scale [RTS], and technological gaps) and technical efficiency vary with disability. As an identification strategy, we utilized statistical matching techniques in creating comparable pairs of disabled and non-disabled farmers. This strategy allows us to directly attribute any observed disparities in crop production technology and technical efficiency to the disability status of the farmers. By leveraging this approach, our study aims to provide a comprehensive understanding of the possible disability-induced technology and efficiency gaps in Ghana's agricultural landscape, highlighting the specific challenges and opportunities that exist for farmers with disability.

The analysis reveals that farmers with disability have an average technological access index of 0.818 compared to 0.938 for their non-disabled peers, culminating into an average disability-induced technology gap of 12.768% in crop production in Ghana. Evaluating the managerial capacity of farmers in each group relative to their respective frontiers reveals an average score of 0.670, suggesting that farmers with and without disability generate, on average, 67% of their attainable frontier outputs. However, against a common benchmark, which is the meta-frontier, we find that farmers with and without disability operate at 57.4 and 63.2% of the industrial frontier, reflecting a 13.396% gap against disabled farmers due to differences in production technology. The disability gap in technology access is likely due to obstacles faced by PWDs in accessing farm intensive margin inputs. Access to agricultural inputs for PWDs is significantly limited by financial barriers, with studies indicating that PWDs face exclusion from microcredit schemes [20], [21] and reduced likelihood of accessing support from formal financial institutions [20].

While our core findings indicate that the overall shortfall in crop production due to disability is robust, the source of this shortfall—whether due to technological endowment (TGR) or technical efficiency (TE)— depends on whose disability we focus on. Specifically, the greater TE scores observed in cases where the "child (adopted or biological) of the farmer only" and "spouse or child of the farmer only" are disabled is offset by larger gaps in TGR. For the disability of other household members, both TE and TGR contribute to the shortfall, with TE being more prominent. This suggests that whilst interventions targeted at improving both technology access and technical efficiency are essential, such interventions should consider the specific member of the household who suffers from disability and their relation to the farmer.

Our research enriches the existing body of literature in multiple significant ways. Notably, while previous studies on production shortfalls in Ghana have predominantly concentrated on factors such as geographical location [22], [23], [24], age of the farm operator [25], and gender [26], we consider a very critical developmental issue of disability in agricultural production. To our knowledge, evidence is not only sparse on this germane developmental issue on the global scale but also notably absent in the discourse on disability parity within the context of SSA. Further, continental studies have only demonstrated gaps in access to land by PWDs with sparse work being done on intensive margin input access and use [27]. Our study expands the scope to include access to intensive margin inputs like planting materials, labor, fertilizer, and agro-chemicals. By delving into this underexplored area, our study not only fills a crucial gap in the literature but also broadens the understanding of the complex interplays affecting agricultural productivity, thereby contributing to a more inclusive approach in agricultural research and policy formulation.

The remainder of this paper is structured as follows. Section 2 outlines the data sources, construction, and presents descriptive statistics to contextualize the study. This section also examines the current state of disabled farmers in Ghana, providing a foundational understanding of their challenges and opportunities. Section 3 details the methods employed and discusses the identification strategy for the empirical investigation. In section 4, we delve into the results and their implications, offering a discussion that situates our findings within broader literature. Finally, the paper concludes in section 5 with a summary of our findings, their significance for policy and practice, weaknesses, and suggestions for future research.

2. Data

2.1 Data sources and construction

This study utilizes farm-level data sourced from the Ghana Living Standards Surveys (GLSS) conducted in 2012/13 (GLSS6) and 2016/17 (GLSS7). These surveys, designed as repeated cross-sectional studies, implement a two-stage sampling methodology, initially selecting enumeration areas, followed by households. The data from GLSS have been consolidated into a comprehensive farmer-level dataset [28], facilitating in-depth analysis of agricultural productivity across various value chains in Ghana [22], [23], [24], [29], [30]. Our analysis is restricted to crop farmers from these surveys, specifically those whose yields (in kg/ha) falls between the 2.5^{th} and 97.5^{th} percentiles, segmented by survey iteration and crop. The final sample comprised 19,862 farm operators cultivating at least one of the following crops: banana, beans, cashew, cassava, citrus fruits, cocoa, coconut, cocoyam, cotton, eggplant, kenaf, maize, millet, okra, onion, palm, peanuts, pepper, plantain, potato, rice, sorghum, sugarcane, tomato, various vegetables, and yam.

The consolidated dataset [28] lacks specific indicators for the disability status of farmers and their household members. To address this gap, we leveraged the dataset's preservation of original enumeration area, household, and member identification variables. Our approach involved constructing disability variables directly from the foundational GLSS and integrating these into the consolidated dataset. Initially, we identified the disability status of individuals across various domains—education, health, employment, and governance—guided by the methodology outlined in Table S1 of the online appendix. Subsequently, we developed an indicator variable that captures the disability status of each farmer, encompassing the disability of the farmer, their immediate family (spouse and children), and other household members. Furthermore, this process included documentation of the specific types of disability identified within these groups. Based on this formulation, 9.43% of the sample had a disability as defined above. This constituted the disability of the farmer (9.42%), their immediate family (4.79%), or other household members (5.48%). Unless specified otherwise, the term 'disabled farmer(s)' used throughout this paper refers to the disability status of the farmer, their immediate family members, and other members of their household.

2.2 Descriptive statistics

This section provides summary statistics of the key variables used in the model. Table 1 presents an overview of crop producers in Ghana, disaggregated by disability status. Approximately 25% of the sampled respondents are female, with an average age and years of education of 47 and 4 years respectively. The average household size per adult equivalent is 5.43, with a dependency ratio of 1.42. In terms of crop production, the average total real value of all crops in our sample is GHS 1,281. Significant variations are observed in the value of selected crops across different categories, including cereals, roots and tubers, legumes, vegetables, starches, and tree crops. Yam production shows the highest crop value (GHS 1,634), while okra has the lowest value (GHS 350). On average, farmers cultivate 1.83 hectares of land, with about 62% of the sampled farm households owning land. Crop diversification, measured at a standard deviation of 0.46, indicates the diversity of crops grown by farmers. The average value of planting materials used per hectare is GHS 135. Household labor per adult equivalent unit stands at 7.17, while the average number of hired labor, fertilizer, and pesticide use per hectare are 20 man-days, 263 kg, and 20 liters, respectively. Only a small percentage of farm households have access to mechanization (5%), irrigation (2%), and credit (12%).

We observed significant differences between disabled and non-disabled farmers in several aspects, including the proportion of females, age, years of education, pepper production, crop diversification, value of seeds, household labor per adult equivalent (AE), quantity of pesticide use, proportion of farmers using mechanization, and household size. Approximately 9% of the disabled farmers are females, compared to 91% of the non-disabled farmers. Disabled farmers are generally older and have fewer years of education, on average. Non-disabled farmers recorded significantly higher production of pepper, value of planting materials, and pesticide use than their disabled counterparts. However, disabled farmers tend to diversify their crop portfolios more and rely more on hired labor than non-disabled farmers. Additionally, a relatively higher proportion of disabled farmers use mechanization services and have larger household sizes relative to non-disabled farmers. The results further highlight that the cultivation of selected crops (maize, rice, millet, sorghum, beans, peanuts, cassava, yam, cocoyam, plantain, okra, tomato, cocoa, and palm) does not differ significantly based on the disability status of the farmer. This suggests that disability may not necessarily create a productivity gap in terms of cultivating these crops. However, this result is only indicative, as there are both observable and unobservable factors that may be influencing the outcomes. In the subsequent section, we employ more robust estimation methods to test this hypothesis comprehensively.

We further show the trend for the respective covariates for the pooled, disabled and non-disabled samples. The pooled sample results show a positive trend of disability in crop production, factor inputs, and institutional factors except for palm, mechanization, irrigation, and credit. Variation exists in the disability trend for crop production, factor inputs, and institutional factors based on the sub-sample (non-disabled and disabled) analysis. Additional details regarding the summary statistics specific to the construct of disability (i.e., disabled close relatives, disabled other members), as well as trends in the characteristics of disabled crop producers, are available in Tables S1 and S2 of the online appendix.

2.3 The state of disabled farmers in Ghana

Table 2 presents the prevalence and trends of disability among Ghanaian crop farmers for the 2012/13 and 2016/17 surveys, categorizing the data by disability types such as Physical, Sight, Hearing, Intellect, Speech, Emotional, and Other. This categorization facilitates a more nuanced understanding of the specific challenges that disabled farmers encounter in their agricultural activities. The data on disability prevalence by crop shows distinct patterns, with millet and sorghum recording the highest overall prevalence rates of 0.116 and 0.112 respectively, whereas crops like eggplant exhibit the lowest of 0.048. This variation suggests that the experience of disability might differ significantly across agricultural contexts, reflecting diverse farming environments and possibly differing community support structures in regions predominantly cultivating these crops. Further analysis of the specific types of disability reveals more about the conditions affecting agricultural productivity. Physical disability is notably more common, as seen in the prevalence rates of millet (0.029) and sorghum (0.037), which could limit the ability of such persons to effectively undertake farm operations. Sight and hearing impairments also show significant rates, especially in millet (Sight: 0.027, Hearing: 0.014) and sorghum (Sight: 0.027, Hearing: 0.015). The lower incidence of reported intellectual (e.g., millet: 0.005, sorghum: 0.004) and emotional disabilities (e.g., millet: 0.004, sorghum: 0.004) may indicate either underreporting or a lack of adequate recognition and diagnostic facilities within rural agricultural communities. This discrepancy highlights the need for more inclusive health and support services that are sensitive to the full spectrum of disabilities, ensuring that all farmers receive the required assistance.

The analysis of the percentage change in headcount ratios for the survey periods for disability among crop farmers in Ghana as shown in Table 2 reveals a complex landscape with significant variations by crop and disability type. Notably, millet shows the largest increase in overall disability prevalence at 4.605%. Conversely, the general category of "Any crop" demonstrates a notable overall decrease in disability prevalence of 5.055%. Physical disability has increased notably among cocoyam farmers, rising by 2.194%. In terms of sensory disabilities, increases are observed in both sight and hearing categories; for instance, banana farmers reported increases in sight disability by 1.636% and hearing by 0.247%, pointing towards the need for enhanced medical support and adaptive technologies in these areas. Interestingly, intellectual and emotional impairments show smaller changes, often negative, as seen for cocoa where intellectual disability declined by 0.660%. Again, this may reflect variability in reporting and diagnosis of these types of disabilities or real changes in prevalence. Some crops, such as eggplant, displayed mixed trends with significant increases in speech disability (2.708%) alongside sharp declines in "Other" disabilities (-3.501%), underscoring the diverse impacts of environmental or social factors on the prevalence of disability among farmers.

3. Methods

3.1 Meta-stochastic frontier analysis

Numerous studies have established that the adoption of agricultural technologies by Ghanaian farmers is influenced by various factors, including geographical location [22], [23], [24], farmer's age [25], and gender [26], among others. In the context of this study, distinct variations in production characteristics which correlate with disability status are observed, as detailed in the online appendix and also summarized in Table 1. These variations suggest that disability status could significantly influence crop production in Ghana.

Firstly, the uptake of farm technologies by disabled farmers is frequently obstructed by physical barriers, since standard farming equipment are typically designed for able-bodied individuals, hence, the growing recognition for assistive and adaptive technologies for farmers with disability [31], [32], [33]. Secondly, disability may reduce a farmer's ability to perform labor-intensive tasks, since most smallholder operations are predominantly manual [34], thereby potentially decreasing the operational efficiency of non-adapted technologies. This inefficiency could result in lower farm output and diminished economic returns. Thirdly, the elevated costs associated with specialized equipment represent a substantial barrier to technology adoption for disabled farmers. Without financial interventions such as subsidies or grants, these costs can be prohibitively high. Consequently, investment decisions by disabled farmers regarding new technologies are strongly influenced by the anticipated return on investment.

Given these considerations, it is crucial to account for technological disparities when evaluating the production performance of farmers in relation to the best practice frontier. Neglecting these disparities may lead to misattributions of production inefficiencies [35]. In our empirical approach, we categorize farmers into two groups—disabled and non-disabled—and apply the Meta-Stochastic Frontier (MSF) analysis using a two-step method [36], which is described in subsequent sections. This methodology enables a nuanced understanding of how disability influences agricultural productivity via technological endowment and the efficacy of technology use.

For each group, we assume a uniform farm production technology, which in conjunction with optimal management practices, position farmers at different points along their group-specific Stochastic Frontiers (SFs). Nonetheless, due to technical inefficiencies or unique disruptions, some farmers may perform below the SF. Additionally, instances of farmers outperforming the SF can occur, attributable solely to positive production shocks which are outside the control of farmers. Following previous studies on crop production in Ghana which used the GLSS [25], [26], [30], [37], and due to its relative flexibility, this study implements the MSF after a statistical test reveals that the SF production function for the j^{th} group is specified as a Translog of the form:

$$f^j(x_{ijt}) = \ln y_{ijt} = \beta_{0r} + \sum_k \beta_{kj} \ln x_{kijt} + \frac{1}{2}\sum_s \sum_k \beta_{skj} log \ln x_{kijt} \ln x_{sijt} + \boldsymbol{\beta}_h \boldsymbol{h}_{ijt} + v_{ijt} - u_{ijt}$$

$$u_{ijt} \sim N^+[0, \exp(\boldsymbol{w}_{ijt}\boldsymbol{\alpha})], \qquad v_{ijt} \sim N(0, \sigma_{vj}^2) \tag{1}$$

where y_{ijt} represents the total value of crop production output for the i^{th} farmer in group j for survey t. Each x_{kijt} denotes the k^{th} input utilized by the i^{th} farmer, encompassing variables such as land, planting materials, both family and hired labor, fertilizer, and pesticides. The vector $\boldsymbol{h}_{ijt}$ contains temporal (GLSS waves) and spatial (ecological zone) production shifters. The terms u_{ijt} and v_{ijt} capture the deviations from the production frontier due to technical inefficiency and idiosyncratic shocks, respectively. A distinctive aspect of the model is the positive skewness assumption for u_{ijt}, suggesting that u_{ijt} could adhere to various distributions, including exponential, half-normal, gamma, and truncated-normal distributions, amongst others. After considering all potential distributions, we opted for a half-normal distribution (i.e., $u_{ijt} \sim N^+\left[0, \exp\left(\boldsymbol{w}_{ijt}\boldsymbol{\alpha}_j\right)\right]$), having encountered issues with convergence for other distributions. Particularly, we assume that the deviation caused by technical inefficiency (u_{ijt}) is modeled as $\sigma_{u_i}^2 = exp(\boldsymbol{w}_i\boldsymbol{\alpha})$, where $\boldsymbol{w}_i$ includes covariates influencing technical inefficiency and $\boldsymbol{\alpha}$ represents a vector of parameters to be estimated. Following previous works [25], [26], [30], [37], $\boldsymbol{w}_{ijt}$ contained farmer characteristics (age, education, and gender), type of disability, institutional factors (land ownership, credit, mechanization, and extension), crop diversification, fixed effects for ecological zone and GLSS waves, and a constant term. Conversely, v_{ijt}, is assumed to follow a normal distribution with zero mean and variance σ_v^2 [$v_{ijt} \sim N\left(0, \sigma_{vj}^2\right)$] [38].

Given the SF production function for the j^{th} group, the "pure farmer technical efficiency" (TE) of the i^{th} farmer is calculated as:

$$TE_{ijt} = E\left[\exp\left(-u_{ijt}\right) | \hat{\varepsilon}_{ijt}\right] \tag{2}$$

To implement the two-step MSF method [36], we first separately estimated output levels for disabled and non-disabled farmer groups. Then, these outputs informed a pooled analysis in the MSF's second step. This process introduces a one-sided error term (u_{Mijt}) in the MSF, representing technology gaps associated with disability. Essentially, the MSF envelops all group-specific frontiers, allowing us to comprehensively analyze the impact of disability on agricultural productivity. The MSF [$f^M\left(x_{ijt}\right)$] which envelops the group-specific stochastic frontiers [$f^j\left(x_{ijt}\right)$] is specified in Equation (3) as:

$$f^M\left(x_{ijt}\right) = \ln \hat{y}_{ijt} = \beta_{0r} + \textstyle\sum_k \beta_{kM} \ln x_{kiMt} + \frac{1}{2}\sum_s \sum_k \beta_{skM} log \ln x_{kiMt} \ln x_{siMt} + \boldsymbol{\beta}_h \boldsymbol{h}_{ijt} - u_{Mijt} \tag{3}$$

Where $u_{iM} \sim N^{+}\left(0, \exp(\boldsymbol{w}_i \boldsymbol{\alpha}_M)\right)$ is strictly positive, implying that $f^{j}\left(x_{ijt}\right) \leq f^{M}\left(x_{ijt}\right)$. Consequently, the ratio of group j's stochastic frontier to the MSF is the technology gap ratio (TGR), which is represented as:

$$TGR_{ijt} = \frac{f^{j}\left(x_{ijt}\right)}{f^{M}\left(x_{ijt}\right)} = e^{-u_{iM}} \leq 1 \qquad (4)$$

The TGR hinges on both the accessibility and level of adoption of the technology, which varies based on individual farm circumstances. The meta-technical efficiency (MTE) serves as an overarching performance metric, quantifying each farmer's technical efficiency relative to the meta-frontier production technology. Essentially, MTE is a composite measure that can be broken down into two components: TE, representing efficiency against group-specific frontiers, and the TGR, indicating the gap between the highest-performing technology available and the utilized technology set. Accordingly, each farmer's MTE is given by equation (5) as follows:

$$MTE_{ijt} = f^{j}\left(x_{ijt}\right)\left[f^{M}\left(x_{ijt}\right)e^{v_{ijt}}\right]^{-1} = TGR_{ijt} \times TE_{ijt} \qquad (5)$$

The SF and meta-frontier parameters were estimated using the "*frontier*" command in Stata 15 through the maximum likelihood estimation technique. Input elasticities were derived as the first derivatives of these frontiers at mean input levels, and the production returns to scale (RTS) were calculated as the sum of these elasticities. Disability-specific TE, TGR, MTE were then calculated using designated equations, providing insights into the impact of disability on farm performance.

3.3 Identification

The debate over using self-reported health and disability indicators in economic and demographic research highlights a crucial methodological issue. These self-assessed measures are potent predictors for various outcomes [39], [40], [41]. They offer a comprehensive view of an individual's health and disability status, more so than what objective indices can provide, functioning almost as "sufficient statistics" with only slight enhancements from additional, objective measures [42]. Nonetheless, concerns about their vulnerability to bias and endogeneity are raised, especially the tendency of respondents to exaggerate their health problems [43], [44]. This issue introduces a classical endogeneity dilemma, casting doubt on the reliability of self-reported measures' predictive power. Therefore, the challenge involves carefully utilizing the rich information provided by self-reported indicators while implementing methodological controls to mitigate potential biases and ensure the integrity of research findings. Our study, relying on self-reported disability measures, addresses these potential selection bias concerns by utilizing a matched sample method to estimate the meta-frontier (Equation [3])—a common approach in studies using MSF that often encounter self-selection bias in technology adoption [45], [46], [47], [48], [49]

Our methodology pairs each farmer with disability with a non-disabled farmer of similar characteristics. Diverging from the traditional matching imputation [50], [51] that replaces missing outcomes with those of a matched unit, our goal is to create a balanced sample for estimating the meta-frontier (Equation [3]). Matching criteria include farmer demographics (age, education, marital status, religion, ethnicity, and relation to the household head), household characteristics (size, dependency, and female ratio), crop diversification, share of land allocated to various crops, and land ownership. Importantly, our observations were paired strictly within the same operator gender, GLSS wave, region, ecology, and rural/urban locality. This careful matching allows us to directly link any technological differences observed to the disability status of farmers.

When matching farms for comparison, simplicity lies in having just one key covariate to consider, where each farm in the treatment group is paired with the closest non-treatment farm based on that single characteristic. However, the complexity escalates with an increase in the number and diversity (both scalar and categorical) of covariates to be matched on. To manage this complexity, we utilize one-to-one nearest-neighbor matching, establishing metrics of similarity to identify comparable pairs. Our metrics for determining the distance between pairs include options such as propensity scores (using Logit, Probit, Complementary log-log, or Cauchit link functions), Euclidean distance, Scaled Euclidean distance, Mahalanobis [52], or Robust Mahalanobis [53], [54] distance. We provide a comprehensive analysis of the balancing diagnostics for these metrics in the appendix (Figure S1), where we examine standardized differences and variance ratios—the ideal values of which are close to zero for differences and close to one for ratios, aligning with literature benchmarks [55], [56]. Our findings, detailed in Figure S1, reveal that distance computed via propensity score with a Probit link function achieves the best balance across these metrics, suggesting it as the most effective method for our matching process.

To estimate standard errors, we utilized a jackknife resampling technique. This involved creating 100 resampled datasets by systematically excluding one Enumeration Area (EA) from each survey in every resampling iteration, effectively pooling the remaining EAs from all surveys for each iteration. This process was conducted independently for each survey. Upon generating these 100 unique resampled datasets, we applied our research methodology (MSF and matching) to each. The variability of our estimates across the resampled datasets was used to calculate the standard errors for estimated parameters and effects.

4. Results and discussion

Our analysis of the impact of disability on agricultural productivity via technology access and use in Ghana is comprehensively detailed across several tables and figures. Table 3 presents our model diagnostics and examines how disability influences input elasticities and crop production variability, highlighting productivity differences between disabled and non-disabled farmers. Table 4 assesses disability parity in technology levels and technical efficiency, considering a range of affected individuals including the farmer, their spouse, biological or adopted children, and other household members. Figure 1 depicts the disability parity in per hectare use of crop production inputs in Ghana. Figure 2 depicts the parity in technology adoption and technical efficiency across various farmer demographics such as gender, age, and education. Figure 3 provides a geographical overview, illustrating these disparities across major crops and administrative regions.

While we delve into the disability parity in production function parameters, technology gaps, and technical efficiency among Ghanaian crop farmers in the main body of this work, discussions on the covariates in the production inefficiency function are presented in the online appendix Note S1 for the sake of brevity.

4.1 Diagnostic tests

After ensuring that our estimated Translog models adhere to the monotonicity and curvature conditions for a well-behaved production function, the results displayed in Table 3 indicate that only 43-52% and 21% of observations, respectively, satisfied these constraints. Despite these limitations at the observation level, the overall positive sign of the elasticities across the sample suggests that, on average, our models exhibit appropriate behavior. This general adherence to expected economic principles demonstrates the robustness of our analytical approach in capturing the dynamics of agricultural production in Ghana. Next, three tests were performed to verify the skewed error specification, which is central to the MSF approach, including the one-sided generalized likelihood-ratio test for technical inefficiency [57] and two skewness tests of the residuals resulting from an OLS estimation [58], [59]. These test results were rejected; thus, the study proceeds with the MSF approach. Furthermore, the likelihood ratio test for the null hypothesis that the non-disabled and disabled production frontiers are similar was rejected, which supports the fact that non-disabled and disabled crop farmers in Ghana operate under heterogeneous technologies and thus, their production performance cannot be compared using the SF estimates.

Table 3 also indicates that the mean of the proportion of crop production variance due to technical inefficiency [$\gamma = \sigma_u^2/\sigma^2$] averaged 0.456 and 0.427 for the non-disabled and disabled, respectively. Since all these ratios are less than 0.50, they suggest that a considerable amount of the observed variation in crop output could not be attributed to the inefficient use of farm inputs but rather to idiosyncrasies such as biotic and abiotic shocks, statistical errors in data measurement, and model specifications. The mean of the estimated γ for the meta-frontier was 0.997, implying that a large proportion of the observed variation in crop output, given the disability and non-disability frontiers, could be attributed to technological gaps.

4.2 Output elasticities

Table 3 illustrates that the responsiveness of total crop output to each factor input is statistically significant at the 1% significance level and consistently shows positive correlations across all models, echoing the findings of several studies in Ghana [24], [25], [26], [37]. In these models, land consistently exerts the largest effect on total farm output, followed sequentially by family labor, planting materials, fertilizer, hired labor, and pesticide. Disaggregated by disability status, the table reveals a slightly lower elasticity of land for disabled farmers (0.563) compared to non-disabled farmers (0.607), a decrease of 4.808%. Conversely, the elasticity of planting materials is marginally higher for disabled farmers (0.052) than for non-disabled farmers (0.049), showing a 3.153% increase. The elasticities of both family and hired labor also show gains for disabled farmers—7.907% for family labor and 8.512% for hired labor, indicating that disabled farmers generally tend to gain more from their labor resources than their non-disabled counterparts. This may likely be a compensatory mechanism for the disabled farmers to make up for physical limitations.

Moreover, the elasticity of fertilizer use is slightly higher among disabled farmers (0.026) compared to non-disabled farmers (0.025), with an increase of 2.987%. The most pronounced difference is for pesticide use, where disabled farmers exhibit an elasticity of 0.017, relative to 0.011 for non-disabled farmers, an increase of 60.063%. This greater returns on pesticide use for disabled farmers may stem from their quest to make a judicious use of chemical inputs to compensate for physical limitations in performing labor-intensive tasks such as pest control and thus, tend to gain more from pesticides than their peers. These elasticity estimates suggest that, despite challenges, factor inputs generally tend to be somewhat more productive for disabled farmers than their non-disabled counterparts, highlighting the potential contributions that PWDs stand to make to agricultural productivity growth in Ghana when adequately supported. Lastly, the returns to scale for disabled farmers (0.902) is slightly lower than that of the non-disabled (0.910), a minor difference of -0.189%. This indicates that both groups are approaching constant returns to scale, though disabled farmers are marginally less efficient at scaling their operations.

4.3 Technology adoption and technical efficiency

The level of technological endowment of farmers with and without disability, which is represented by the estimated technology gap ratios (TGRs) is summarized in Table 3. Findings from the matched sample reveal an average TGR of 0.938 and 0.818 for the non-disabled and disabled farmers, respectively. This implies that farms managed by persons with and without disability generally produce, on average, 81.8 and 93.8% of the potential industrial output, respectively. This culminates into a statistically significant 12.768% disability-induced technology gap in crop production in Ghana. Consequently, in order to rake in the same level of farm output as their peers, disabled farmers may have to raise their farm technology by an average of 12.768%. Evaluating farm performance of each farmer group relative to its own technology, which is represented by the pure farmer technical efficiency (TE) scores as displayed in Table 3 reveal an average score of 0.670 for both groups. This indicates that, on average, farmers with and without disability produce 67% of their respective potential frontier outputs, given their current individual farm technologies. This finding is consistent with those reported by recent empirical studies on Ghana in particular and Africa in general [25], [37], [60], [61], [62], which reveal that smallholder farmers in developing countries generally produce beneath their technically efficient frontiers.

Combining the TGR and TE effects into a single comparable measure (meta-frontier technical efficiency [MTE = TE × TGR] scores) across both groups shows that farmers with and without disability operate at 57.4% and 63.2% of the industrial frontier, respectively. This corresponds to a statistically significant MTE difference of 13.396%, indicating that disabled farmers are generally 13.396% less efficient than their non-disabled peers. Since both groups have similar TE scores relative to their individual group frontiers, the prime source of the variation in the estimated MTE for farmers with and without disability can be attributed entirely to disability-driven differences in technological endowment.

The disability gap of approximately 13% in technology access can be attributed to the significant obstacles faced by PWDs in accessing farm inputs and institutional support. For instance, in Zimbabwe, PWDs encounter political and structural barriers that limit their access to land and agrarian support [27]. Similarly, in Nigeria, PWDs report inadequate access to appropriate technology, highlighting systemic issues that hinder their participation in social and economic activities [63]. Further, evidence from Ghana indicates that PWDs face considerable barriers, including difficulties in accessing farmlands, farming tools, credit and negative societal attitudes, which tend to limit their inclusion and participation in farming [16]. In Figure 1 from our sample, which is presented in the appendix and based on the matched dataset, we find that disability status significantly influences the usage rates of various crop production inputs. Notable correlations between disability and agricultural production inputs include decline in the per hectare use of planting materials (-53.50%), pesticides (-41.80%), fertilizer (-36.77%), hired labor (-17.83%), and family labor (-8.05%). Conversely, the difference in land area between disabled and non-disabled farmers is statistically similar. These outcomes suggest that the disability of farmers and their household members significantly influences their crop production technology mix relative to their intensive margin.

Access to agricultural inputs for PWDs can be significantly limited by financial constraints, as evidenced by various studies. In Uganda, barriers to microcredit access for disabled persons include exclusion by staff and non-disabled members of credit groups, self-exclusion, exclusion by credit design, and disability itself, with credit design being the most significant obstacle [21]. Similarly, in Ghana, research indicates that being disabled reduces the likelihood of accessing and using formal financial institutions, with PWDs being significantly less likely to use commercial and rural banks. However, they are more likely to utilize mobile money services [64]. Additionally, PWDs tend to rely more on informal self-help schemes than formal microfinance services, accessing more savings than loans [20]. Financial barriers highlight the systemic challenges that PWDs face in accessing the necessary resources to fully participate in agricultural activities.

4.4 Robustness of main findings

Next, we evaluate the robustness of the disability gap in crop production linked to technological endowment across various dimensions of the empirical analysis. First, we consider the measure of disability. In our main specification, a farmer's disability status was broadly defined to include the farmer, their immediate family (spouse and children), or household members. When we narrowly restrict the disability indicator to capture the exclusive disability of individuals, Table 4 shows that the disability gap in technology access persists, with levels varying from -1.612% for household members other than the spouse or child to -31.592% for the farmer's child (adopted or biological). However, when examining TE, significant differences emerge, unlike the case of the broadly defined indicator where the difference was insignificant. Specifically, we find that a farmer with a disabled spouse or household member other than the spouse or child has a TE that is 15.13% and 5.59% lower than the base category (farmer without any disabled individual in their household), respectively. Conversely, compared to the base category, we find higher TE scores when the disability exclusively includes only the child (adopted or biological) of the farmer (24.13%) or only the spouse or child of the farmer (18.046%).

Ultimately, regardless of the divergence in the exclusively estimated gaps in TGR and TE from the broadly defined ones, we observe MTE ranging from -10.56% (farmer only disability) to -18.21% (spouse of farmer only disability). These exclusively estimated MTE gaps are statistically like the broadly defined gap of -13%, highlighting that while the overall observed shortfall in crop production is robust regardless of whose disability is considered, the source (TGR vs TE) of this shortfall depends on who’s disability we focus on. In cases where "child (adopted or biological) of the farmer only" and "spouse or child of the farmer only" are disabled, production gains tied to relatively higher TE for PWDs are eroded by substantially larger gaps in technology access (TGR). For all other exclusive disabilities, both TE and TGR contribute to the shortfall, with the former being more prominent. These diverging results suggest that targeted interventions to improve both technology access and technical efficiency are essential, particularly when considering the disability of specific members of the household.

When disability is kept as broadly defined to include all household members, our core findings on the gaps in TGR, TE, and MTE remain robust across various dimensions: (1) the choice of production function, distributional assumption on the inefficiency term, calculation method for observational level scores (TGR, TE, and MTE), central tendency estimation of observational level scores, matching algorithm, and whether the production function is restricted or freely estimated (see Figure S2). The only exception is when we use a truncated skewed Laplace distribution for the inefficiency term, where we find relatively higher gaps against PWDs in MTE and TGR but a positive differential in TE, albeit statistically like the preferred assumption of a half-normal distribution. Other notable exceptions include relatively higher gaps in MTE when an unrestricted production function is estimated and when observational level values are aggregated by taking the median. Overall, the pattern of results from the robustness checks in Table 4 and S2 are consistent with the main findings.

4.4 Observed heterogeneity

Figures 2 and 3 report the disability gap in TGR, TE, and MTE across various observable characteristics, including farmer's gender, age, education, crop produced, and regional location. For each dimension of heterogeneity, we summarize the observation level TGR, TE, and MTE estimated using the entire matched sample, without implementing separate MSF along the disability dimension for each level of a given heterogeneity variable. We find that the disability gap in crop production and its attribution do not significantly change by gender or age, except for farmers over 59 years old and those with senior secondary school education, where the attribution of the disability gap is smaller due to notable gains in TE. At the crop level, the disability gap in

MTE against disabled farmers is robust across all crops, with the highest gaps observed in oil palm (-30.35%), followed by okra (-20.47%), pepper (-17.96%), beans (-17.77%), rice (-16.78%), tomato (-16.68%), sorghum (-15.33%), millet (-14.44%), other crops (-14.34%), yam (-13.63%), cocoyam (-12.89%), peanut (-12.01%), maize (-11.57%), plantain (-11.33%), cassava (-11.1%), and cocoa (-8.68%). Regional differences show the highest disability gap in Greater Accra at -19.21%, followed by Upper East (-17.17%), Northern (-14.36%), Ashanti (-14.24%), Upper West (-13.93%), Central (-11.71%), Western (-11.24%), Eastern (-11.14%), Volta (-8.96%), and Brong Ahafo (-6.67%).

5. Conclusion

In this paper, we extend the literature on productivity analysis by accounting for the disparity in technology usage and crop production efficiency between farmers with and without disability in Ghana. Most of the empirical studies on productivity analysis have been very insightful and informative. However, the role of disability in agricultural production analysis is less explored, especially in the era of changing demographics, discrimination, unemployment, and broader societal hardships faced by PWDs. This study employs the meta-stochastic frontier analysis and matching techniques on farm-level data for 2012/13 and 2016/17 to assess the degree of disparity in agricultural technology level and technical efficiency based on disability and further explore how this disparity varies based on different demographics and agricultural contexts. We find that there are negligible differences in technical efficiency (<0.5%) between disabled and non-disabled farmers. This suggests that, when given equal access to resources, disabled farmers are just as efficient as their non-disabled counterparts. However, the study also uncovers a significant disparity in the productive capacity of technology used by disabled farmers, which is 13 percentage points lower than that of non-disabled farmers. This results in a 13% production disadvantage for disabled farmers.

This production gap among disabled farmers primarily results from limited access to essential agricultural inputs like planting materials, labor, fertilizer, and agro-chemicals per hectare. This technology gap not only exposes significant inequalities but also marks a critical area for targeted interventions. These interventions should focus on enhancing both inclusivity and productivity for disabled individuals in agriculture by ensuring they have the same access to resources and technologies as their non-disabled counterparts. Addressing this issue is crucial for several reasons. Firstly, promoting inclusivity within agriculture can help alleviate the broader social and economic exclusion faced by disabled individuals. Secondly, boosting the productivity of disabled farmers can significantly enhance overall agricultural output and contribute to economic growth, which is vital for countries like Ghana where agriculture is a key economic sector. Lastly, ensuring equitable access to agricultural technologies and resources for disabled farmers supports global goals for sustainable and inclusive development.

Some caveats to the analysis are worth mentioning. First, the analysis faced challenges in identifying suitable instruments that met the exclusion restriction criteria, leading to the use of matching techniques instead of an ideal instrumental variable. Matching improved balance and comparability between disabled and non-disabled farmers, reducing reliance on the model's functional form and diminishing the effects of omitted variable bias. Thus, the findings should be viewed as a detailed examination of the relationship between disability and production rather than a definitive demonstration of causality. Secondly, the definition of a farmer's disability status was broad, encompassing not only the farmer but also immediate family members such as spouses and children, or other household members. Although we applied more narrowly defined statuses in our robustness checks, this broad definition is crucial to consider when interpreting our results. The specific household member affected by disability and their relationship to the farmer can significantly influence which interventions are appropriate.

Despite these limitations, the findings of this study underscore the urgent need for targeted policy interventions to close the technology gap and ensure equitable access to agricultural inputs for disabled farmers. Such measures are essential not only for advancing social justice but also for fostering a more productive and resilient agricultural sector in Ghana and across the broader sub-Saharan African region. By addressing these disparities, we can move closer to achieving sustainable agricultural development that benefits all members of society, regardless of physical abilities.

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Tables and Figures

Table 1. Summary Statistics of Crop Producers in Ghana (2012-2017)

Variable	Mean (SD)			Trend (%) [a]		
	Pooled (n= 19,862)	**Not disabled (n= 17,990)**	**Disabled (n= 1,872)**	**Pooled (n= 19,862)**	**Not disabled (n= 17,990)**	**Disabled (n= 1,872)**
Farmer						
Female farmer (dummy)	0.25 (0.43)	0.91 (0.29)	0.09 (0.29)	-1.45** [0.68]	0.54*** [0.15] †	-5.21*** [1.42] †
Age (years)	47.33 (15.16)	46.88 (15.03)	51.67 (15.80)	0.63*** [0.13]	0.66*** [0.14] †	0.34 [0.44] †
Education (years)	4.49 (5.16)	4.58 (5.17)	3.69 (4.98)	2.66*** [0.51]	2.68*** [0.52] †	2.48 [2.09] †
Selected crop production						
All crops (real GH₵/ha)	1280.84 (1734.43)	1293.19 (1741.43) †	1162.17 (1661.40) †	11.67*** [0.61]	11.99*** [0.63] †	8.66*** [2.21] †
Maize (Kg/ha)	2531.11 (7238.73)	2575.22 (7415.95) †	2106.32 (5216.84) †	30.19*** [2.18]	31.54*** [2.34]	17.60*** [5.64]
Rice (Kg/ha)	1184.07 (2038.12)	1185.49 (2011.76) †	1172.39 (2246.54) †	12.81*** [1.91]	11.64*** [1.88] †	21.96*** [8.03] †
Millet (Kg/ha)	894.88 (1335.52)	895.62 (1308.23) †	889.16 (1530.36) †	1.48 [1.30]	1.81 [1.38] †	-1.05 [3.89] †
Sorghum (Kg/ha)	883.78 (1223.74)	895.87 (1223.56) †	787.68 (1223.27) †	0.67 [1.44]	1.48 [1.51] †	-5.92 [4.71] †
Beans (Kg/ha)	947.63 (1715.62)	951.73 (1679.98) †	914.05 (1986.05) †	8.99*** [1.63]	8.88*** [1.64] †	9.90 [6.59] †
Peanut (Kg/ha)	1239.47 (2502.86)	1236.52 (2473.55) †	1266.63 (2761.03) †	17.43*** [1.81]	17.31*** [1.85] †	18.51*** [7.07] †
Cassava (Kg/ha)	1361.29 (2781.28)	1351.48 (2745.72) †	1474.63 (3165.37) †	69.70*** [7.63]	70.52*** [8.14] †	60.65*** [19.21] †
Yam (Kg/ha)	1634.16 (2870.58)	1612.19 (2843.48) †	1919.36 (3201.42) †	287.46 [301.51]	299.64 [332.13] †	172.21 [277.81] †
Cocoyam (Kg/ha)	477.47 (1065.11)	492.52 (1089.97) †	244.78 (508.43) †	47.95* [25.19]	47.44* [27.50] †	41.22 [32.46] †
Plantain (Kg/ha)	1037.24 (2061.35)	1041.83 (2073.86) †	975.03 (1888.43) †	96.91*** [25.29]	100.91*** [27.58] †	52.37*** [19.81] †
Pepper (Kg/ha)	664.36 (1470.13)	680.84 (1500.29)	470.07 (1040.26)	12.00 [16.74]	4.55 [19.20]	37.60*** [11.79]
Okra (kg/ha)	350.26 (658.73)	345.88 (638.68) †	389.98 (825.40) †	7.36* [4.27]	8.16* [4.50] †	0.25 [13.87] †
Tomato (kg/ha)	526.99 (1280.09)	522.25 (1304.22) †	598.01 (863.44) †	6.74 [10.07]	6.96 [10.70] †	3.54 [16.71] †
Cocoa (Kg/ha)	650.12 (1593.15)	668.17 (1636.63) †	435.72 (908.55) †	35.00*** [4.23]	37.16*** [4.56]	10.70 [8.04]
Palm (Kg/ha)	1139.80 (3473.80)	1159.39 (3549.63) †	873.49 (2212.93) †	-17.57 [90.87]	-17.45 [92.13] †	-22.39 [557.88] †
Land (ha)	1.83 (2.41)	1.83 (2.41) †	1.77 (2.50) †	2.13*** [0.51]	1.80*** [0.52] †	5.22*** [1.91] †
Land owned (dummy)	0.62 (0.49)	0.62 (0.49) †	0.63 (0.48) †	3.68*** [0.32]	3.67*** [0.34] †	3.79*** [1.05] †
Crop diversification (index)	0.46 (0.26)	0.46 (0.26)	0.49 (0.25)	-3.51*** [0.24]	-3.51*** [0.25] †	-3.49*** [0.76] †
Seed (real GH₵/ha)	135.12 (684.10)	139.17 (709.58)	96.21 (353.76)	52.62*** [5.40]	55.42*** [5.96]	27.69*** [6.99]
Household labor (AE)	7.17 (6.69)	7.06 (6.56)	8.24 (7.74)	8.66*** [0.40]	8.42*** [0.42]	10.86*** [1.41]
Hired labor (man-days/ha)	20.03 (78.85)	20.11 (72.25) †	19.32 (125.74) †	5.44*** [1.56]	6.13*** [1.48] †	-1.14 [8.59] †
Fertilizer (Kg/ha)	263.20 (7154.01)	270.50 (7506.50) †	193.06 (1231.44) †	28.54* [14.77]	28.26* [16.28] †	31.11* [18.59] †
Pesticide (Liter/ha)	19.51 (295.07)	20.11 (309.57)	13.68 (53.02)	10.54 [6.71]	10.34 [7.38] †	12.40 [8.23] †
Mechanization (dummy)	0.05 (0.21)	0.04 (0.21)	0.08 (0.27)	-4.09** [2.05]	-3.22 [2.20] †	-12.48** [5.05] †
Irrigation (dummy)	0.02 (0.14)	0.02 (0.14) †	0.02 (0.15) †	-1.39 [3.27]	-1.24 [3.39] †	-2.84 [11.95] †
Credit (dummy)	0.12 (0.33)	0.12 (0.33) †	0.12 (0.32) †	-0.35 [1.18]	-0.94 [1.23] †	5.25 [4.17] †
Household						
Size (AE)	5.45 (3.17)	5.37 (3.14)	6.21 (3.38)	-0.74*** [0.27]	-0.73** [0.29] †	-0.84 [0.83] †
Dependency (ratio)	1.42 (1.70)	1.42 (1.70)	1.42 (1.65)	-1.78*** [0.52]	-2.29*** [0.54]	3.17* [1.85]

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across disability status.

[a] The trend was estimated via a linear regression for continuous variables and a logit model for dummies.

The mean mid-rate interbank FX rate between the Ghana cedi (GH₵) and the US Dollar ($) for December 2019 was 5.54 GH₵/$ as reported by the Bank of Ghana

Data Sources: Ghana Living Standards Survey [waves 6-7]

Table 2: Disability Prevalence Amongst Ghanaian Crop Farmers (2012-2017)

Crop	Type of disability							
	Any	**Physical**	**Sight**	**Hearing**	**Intellect**	**Speech**	**Emotional**	**Other**
	Headcount ratio over the periods 2012/13 and 2016/17							
Millet	0.116 (0.320)	0.029 (0.168)	0.027 (0.163)	0.014 (0.116)	0.005 (0.070)	0.010 (0.098)	0.004 (0.062)	0.034 (0.180)
Sorghum	0.112 (0.315)	0.037 (0.188)	0.027 (0.161)	0.015 (0.120)	0.004 (0.065)	0.010 (0.099)	0.004 (0.062)	0.023 (0.151)
Rice	0.109 (0.311)	0.030 (0.171)	0.023 (0.150)	0.009 (0.097)	0.005 (0.073)	0.007 (0.082)	0.004 (0.062)	0.034 (0.181)
Okra	0.099 (0.299)	0.020 (0.141)	0.012 (0.110)	0.012 (0.110)	-	0.016 (0.126)	-	0.037 (0.188)
Maize	0.094 (0.292)	0.027 (0.162)	0.018 (0.133)	0.011 (0.103)	0.006 (0.076)	0.008 (0.091)	0.003 (0.054)	0.025 (0.155)
Beans	0.109 (0.311)	0.033 (0.179)	0.024 (0.155)	0.011 (0.103)	0.006 (0.078)	0.012 (0.108)	0.003 (0.050)	0.025 (0.156)
Any crop	0.094 (0.292)	0.027 (0.163)	0.019 (0.137)	0.011 (0.105)	0.006 (0.077)	0.009 (0.092)	0.003 (0.054)	0.022 (0.148)
Peanut	0.098 (0.297)	0.029 (0.169)	0.024 (0.152)	0.011 (0.106)	0.006 (0.075)	0.009 (0.096)	0.002 (0.046)	0.019 (0.136)
Cocoa	0.078 (0.268)	0.026 (0.159)	0.015 (0.120)	0.009 (0.095)	0.005 (0.074)	0.005 (0.069)	0.003 (0.054)	0.016 (0.127)
Cassava	0.080 (0.271)	0.022 (0.148)	0.012 (0.109)	0.009 (0.093)	0.007 (0.081)	0.008 (0.087)	-	0.022 (0.145)
Banana	0.112 (0.317)	0.028 (0.166)	-	0.019 (0.136)	-	-	-	-
Plantain	0.069 (0.253)	0.022 (0.147)	0.010 (0.100)	0.006 (0.076)	0.007 (0.084)	0.006 (0.076)	-	0.016 (0.127)
Pepper	0.078 (0.269)	0.015 (0.123)	0.014 (0.118)	0.006 (0.077)	0.007 (0.084)	0.007 (0.084)	0.004 (0.060)	0.026 (0.159)
Yam	0.072 (0.258)	0.019 (0.136)	0.013 (0.112)	0.008 (0.092)	0.004 (0.065)	0.006 (0.078)	0.002 (0.043)	0.020 (0.140)
Cocoyam	0.061 (0.239)	0.022 (0.148)	0.016 (0.126)	-	-	0.006 (0.078)	-	0.006 (0.078)
Tomato	0.063 (0.243)	0.011 (0.105)	0.007 (0.086)	-	-	-	-	0.026 (0.159)
Eggplant	0.048 (0.214)	0.012 (0.109)	-	-	-	-	-	-
Palm	0.069 (0.253)	0.015 (0.121)	0.004 (0.061)	0.011 (0.105)	0.015 (0.121)	0.006 (0.074)	-	0.017 (0.128)
	Percentage change in headcount ratio from 2012/13 and 2016/17							
Banana	-5.055 [6.515]	-3.223 [3.640]	-	-0.842 [2.818]	-	-	-	-
Cocoyam	2.174 [2.125]	1.641 [1.289]	0.525 [1.125]	-	-	0.299 [0.687]	-	0.299 [0.687]
Plantain	-0.090 [1.059]	1.687 [0.630]	0.729 [0.401]	0.103 [0.312]	-0.668 [0.353]	-0.401 [0.319]	-	-1.779 [0.534]
Eggplant	4.605 [3.680]	0.525 [1.803]	-	-	-	-	-	-
Palm	-1.368 [2.247]	0.986 [0.993]	-0.136 [0.549]	0.357 [0.891]	-0.544 [1.091]	0.178 [0.632]	-	-2.524 [1.255]
Cassava	0.986 [0.818]	1.183 [0.448]	0.761 [0.330]	0.649 [0.285]	-0.300 [0.240]	0.262 [0.263]	-	-1.827 [0.438]
Okra	0.358 [2.879]	0.323 [1.283]	-0.623 [0.971]	1.010 [1.023]	-	2.708 [1.599]	-	-3.501 [1.626]
Yam	0.160 [1.292]	1.043 [0.693]	-0.078 [0.554]	0.439 [0.505]	-0.271 [0.310]	0.384 [0.398]	-0.081 [0.206]	-1.385 [0.666]
Cocoa	1.112 [1.093]	1.741 [0.606]	0.376 [0.471]	0.050 [0.390]	-0.660 [0.354]	0.052 [0.284]	0.273 [0.197]	-0.830 [0.562]
Maize	1.179 [0.585]	0.498 [0.319]	0.990 [0.262]	0.302 [0.204]	0.173 [0.149]	0.485 [0.177]	0.179 [0.102]	-1.602 [0.326]
Any crop	1.841 [0.532]	0.795 [0.287]	1.207 [0.246]	0.449 [0.191]	-0.053 [0.148]	0.436 [0.164]	0.214 [0.091]	-1.219 [0.281]
Pepper	0.908 [2.141]	0.323 [0.927]	-0.028 [0.860]	0.695 [0.656]	-0.544 [0.531]	1.046 [1.127]	0.523 [0.526]	-1.287 [1.065]
Peanut	2.999 [0.922]	0.873 [0.524]	1.613 [0.450]	0.699 [0.313]	0.571 [0.238]	0.629 [0.297]	0.166 [0.132]	-1.499 [0.451]
Beans	1.569 [1.139]	1.056 [0.631]	0.997 [0.541]	0.706 [0.363]	0.268 [0.270]	0.481 [0.429]	0.051 [0.179]	-1.943 [0.602]
Tomato	0.000 [2.988]	-0.357 [1.252]	0.268 [1.087]	-	-	-	-	0.179 [1.966]
Rice	1.507 [1.233]	0.675 [0.662]	0.738 [0.586]	0.085 [0.380]	0.764 [0.269]	0.248 [0.316]	0.190 [0.233]	-1.315 [0.750]
Millet	3.284 [1.194]	0.230 [0.631]	1.636 [0.600]	0.247 [0.432]	0.714 [0.234]	0.858 [0.348]	0.245 [0.223]	-0.829 [0.697]
Sorghum	3.230 [1.334]	2.194 [0.779]	1.236 [0.669]	0.534 [0.498]	0.177 [0.272]	1.302 [0.506]	-0.081 [0.257]	-2.036 [0.622]

Standard deviations are in parenthesis and standard errors are in brackets

Data Sources: Ghana Living Standards Survey [waves 6-7]

Table 3. Disability Impact on Input Elasticities and Variability in Crop Production in Ghana (2012-2017)

	Naïve national frontier	Group frontier			Meta-frontier	
		Nondisabled [A]	Disabled [B]	Difference (%) $[(B-A)/A]$	Matched	Unmatched
Elasticity						
Land	0.604*** (0.001)	0.607*** (0.001)	0.563*** (0.001)	-4.808*** (0.205)	0.578*** (0.002)	0.604*** (0.001)
Planting material	0.049*** (0.000)	0.049*** (0.000)	0.052*** (0.000)	3.153*** (0.627)	0.050*** (0.000)	0.049*** (0.000)
Family labor	0.197*** (0.000)	0.198*** (0.000)	0.222*** (0.002)	7.907*** (0.799)	0.211*** (0.001)	0.200*** (0.001)
Hired labor	0.020*** (0.000)	0.020*** (0.000)	0.021*** (0.000)	8.512*** (1.351)	0.021*** (0.000)	0.020*** (0.000)
Fertilizer	0.026*** (0.000)	0.025*** (0.000)	0.026*** (0.000)	2.987** (1.432)	0.026*** (0.000)	0.025*** (0.000)
Pesticide	0.011*** (0.000)	0.011*** (0.000)	0.017*** (0.000)	60.063*** (1.544)	0.014*** (0.000)	0.011*** (0.000)
Returns to scale	0.908*** (0.001)	0.910*** (0.001)	0.902*** (0.002)	-0.189 (0.195)	0.900*** (0.002)	0.909*** (0.001)
Technology/efficiency						
Technology gap ratio (TGR)						
Matched	-	0.938*** (0.009)	0.818*** (0.022)	-12.768*** (3.024)	-	-
Unmatched	-	0.973*** (0.002)	0.850*** (0.025)	-12.684*** (2.668)	-	-
Pure farmer technical efficiency (TE)						
Matched	0.672*** (0.025)	0.673*** (0.018)	0.676*** (0.023)	0.489 (3.069)	-	-
Unmatched	0.680*** (0.028)	0.676*** (0.021)	0.676*** (0.023)	-0.018 (3.140)	-	-
Meta-frontier technical efficiency (MTE)						
Matched	0.590*** (0.013)	0.632*** (0.014)	0.547*** (0.012)	-13.396*** (0.376)	-	-
Unmatched	0.651*** (0.020)	0.658*** (0.021)	0.569*** (0.014)	-13.617*** (0.680)	-	-
Model diagnostics						
Sample size	19862	17990	1872	-	3744	19862
Monotonicity satisfaction rate	43.60	52.30	52.94	-	99.92	99.98
Curvature satisfaction rate	21.96	21.98	21.58	-	35.52	21.97
Schmidt & Lin (1984) [a]	-0.024***	-0.038***	0.138***	-	-0.072***	-4.614***
Coelli, (1995) [a]	-1.366	-2.073**	2.436**	-	-1.801*	-265.459***
Gutierrez (2001) [a]	1308.489**	1219.933**	116.657**	-	1076.780**	16425.228**
Log likelihood	-26845	-24342	-2456	-	3631	35310
No. of parameters	32	32	32	-	32	32
Meta frontier LR test	-	-	-	-	7355.810***	70713.997***
Ratio variance due to inefficiency	0.444*** (0.032)	0.456*** (0.024)	0.427*** (0.030)	-	0.997*** (0.004)	0.956*** (0.040)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

[a] Null hypothesis of no one-sided error (i.e., no inefficiency) was tested.

Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).

Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample.

Table 4. Disability Parity in Technology Level and Technical Efficiency Based on Person Disabled

	Nondisabled **[A]**	**Disabled** **[B]**	**Difference (%)** $[(B-A)/A]$
Technology gap ratio (TGR)			
Anyone including farmer	0.938*** (0.009)	0.818*** (0.022)	-12.768*** (3.024)
Farmer	0.986*** (0.003)	0.963*** (0.010)	-2.314*** (0.731)
Spouse of farmer	0.984*** (0.007)	0.952*** (0.018)	-3.236*** (1.168)
Child (adopted or biological) of farmer	0.946*** (0.003)	0.647*** (0.025)	-31.592*** (2.701)
Spouse or child of farmer	0.960*** (0.005)	0.672*** (0.021)	-30.047*** (2.549)
Household member other than spouse or child	0.856*** (0.021)	0.842*** (0.005)	-1.612 (3.463)
Pure farmer technical efficiency (TE)			
Anyone including farmer	0.673*** (0.018)	0.676*** (0.023)	0.489 (3.069)
Farmer	0.676*** (0.024)	0.629*** (0.003)	-7.079** (2.724)
Spouse of farmer	0.676*** (0.024)	0.574*** (0.002)	-15.132*** (2.574)
Child (adopted or biological) of farmer	0.673*** (0.020)	0.835*** (0.003)	24.126*** (3.312)
Spouse or child of farmer	0.673*** (0.020)	0.795*** (0.002)	18.056*** (3.123)
Household member other than spouse or child	0.673*** (0.020)	0.635*** (0.001)	-5.587** (2.459)
Meta-frontier technical efficiency (MTE)			
Anyone including farmer	0.632*** (0.014)	0.547*** (0.012)	-13.396*** (0.376)
Farmer	0.666*** (0.025)	0.595*** (0.008)	-10.563*** (1.964)
Spouse of farmer	0.666*** (0.026)	0.544*** (0.011)	-18.214*** (2.267)
Child (adopted or biological) of farmer	0.635*** (0.019)	0.551*** (0.020)	-13.209*** (0.540)
Spouse or child of farmer	0.644*** (0.017)	0.541*** (0.016)	-16.066*** (0.265)
Household member other than spouse or child	0.590*** (0.002)	0.524*** (0.003)	-11.144*** (0.257)

Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$
Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).
Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample.

Figure 1. Crop Production Input and Output Disability Gaps in Ghana

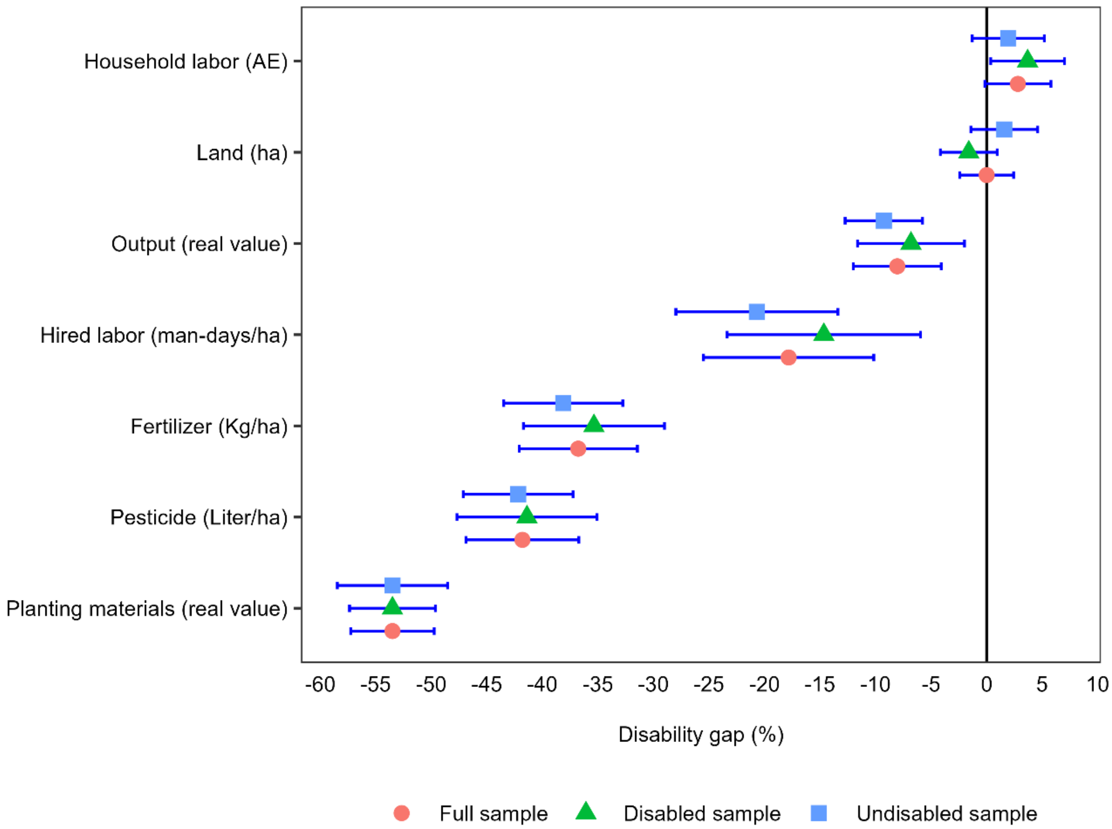


Figure 2. Disability Parity in Crop Production Technology Adoption and Technical Efficiency by Farmer Gender, Age, and Education in Ghana (2012-2017)

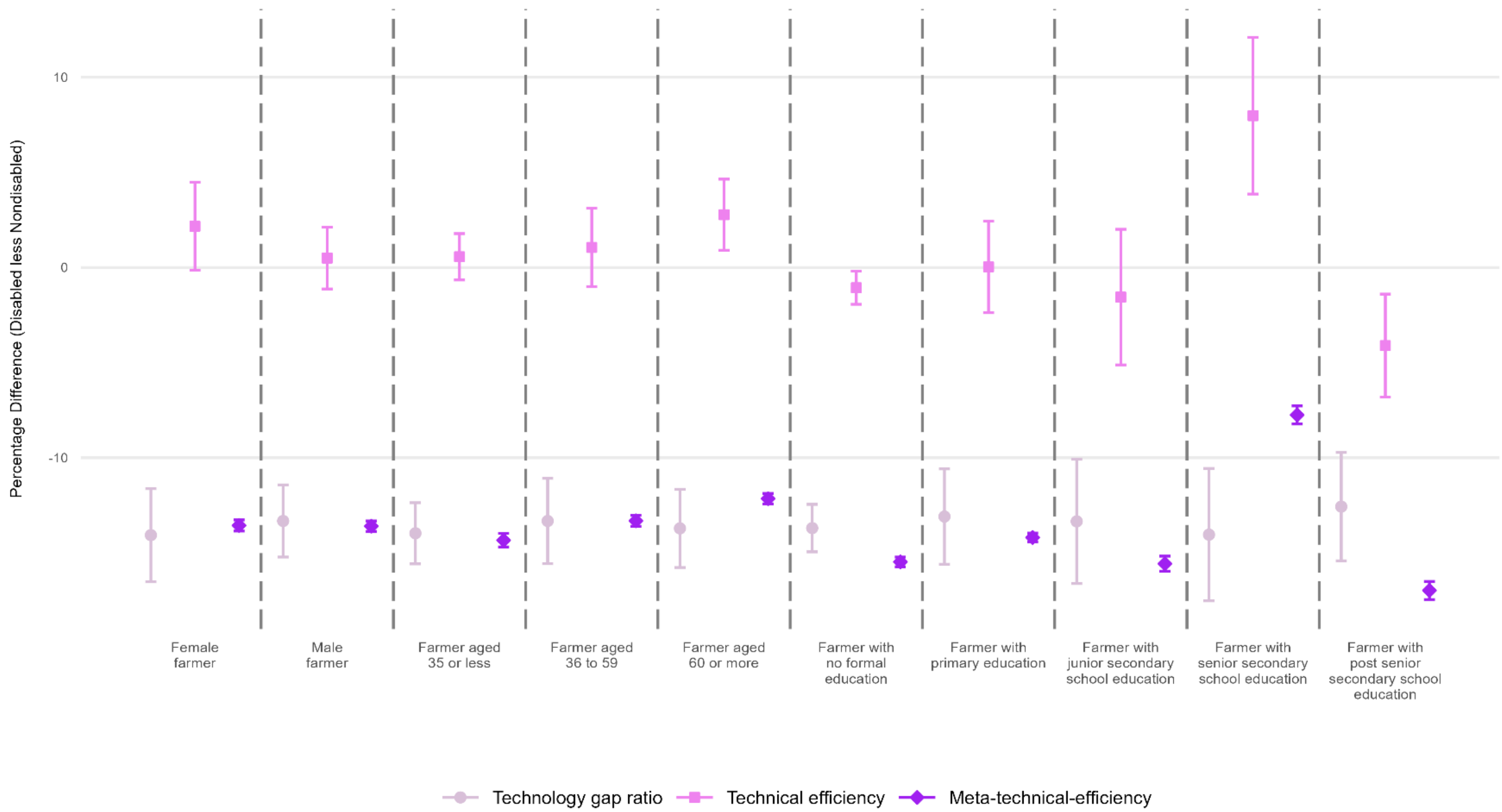
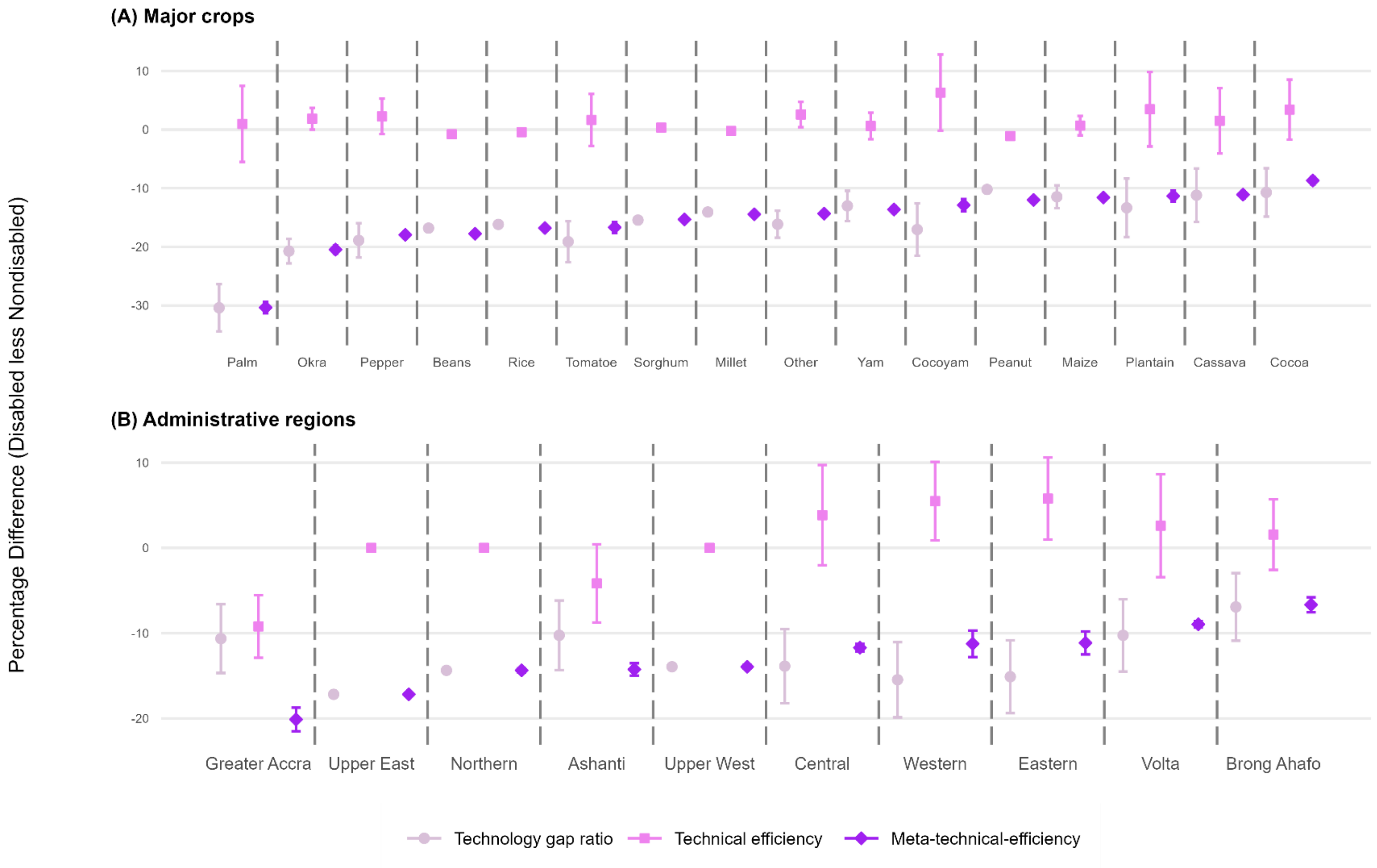


Figure 3. Disability Parity in Crop Production Technology Adoption and Technical Efficiency by Major Crops and Administrative Regions in Ghana (2012-2017)



Appendix

Note S1 Drivers of technical inefficiency

Table S5 outlines the underlying factors that drive farm household's movement towards or away from their respective technically efficient frontiers. We find that regardless of the disability status of the household, being a female, an aged farmer, having more years of education and engaging in crop diversity tend to drive farm households further away from their technically feasible frontiers (Asravor et al., 2024; Tsiboe et al., 2022). Our results further indicate that enhancing farm household's access to mechanization and extension advisory services have the tendency to drive such farm households towards their efficient frontiers, irrespective of their disability status (Tsiboe et al., 2022). We however find mixed evidence for land ownership and access to credit for households with and without disability. Whereas access to credit tends to drive nondisabled households away from their efficient frontier, it drives disabled households towards their efficient frontier. Additionally, disabled farmers who owned farmlands tend to be technically less efficient. Consistent with Tsiboe et al. (2022) and Asravor et al. (2019), the agro-ecological zone of farm households determines their location with respect to their respective efficient frontiers. Whereas being in the Forest and Transitional zones tend to drive farmers away from their respective frontiers, those found in the Guinea and Sudan Savannah zones tend to move towards their respective efficient frontiers, regardless of their disability status.

Table S1. Disability variable construction

Question	Formulation	
	GLSS6	GLSS7
Disability status indicator [takes on 1 if any of the conditions are met, 0 otherwise]		
What is/was the main reason why (NAME) has never attended school?	s2aq1a = 2	s2aq1a = 2
Does (NAME) have any serious disability that limits his/her full participation in life activities (such as mobility, work, social life, etc.)	s3aq26 = 1	s3aq26 = 1
Why has (NAME) not made any effort to find work or start a business? [7 DAYS] {Disabled or unable to work (handicapped}	s4dq4 = 10	s4eq3 = 10
Why was (NAME) not available for work during the last 7 days or within the next 4 weeks days? [7 DAYS]	s4dq10 = 5	s4eq10 = 5
What was (NAME) doing when not available and not seeking for work? [12 MONTHS]	s4gq7 = 3	-
Regarding the provision of public security services, have you ever been discriminated against because of your Disability	s13cq27g = 1	s13cq28g = 1
Was not allowed to participate in any community level activities because of Disability	s13fq9 = 9	s13fq9 = 9
Type of disability		
What type of disability does (NAME) have?	s4gq7	s3aq27i

Table S2. Summary Statistics of Crop Producers in Ghana (2012-2017)

Variable	Pooled (n=19862)	Disabled person				
		Farmer (n=625)	Spouse of farmer (n=313)	Child (adopted or biological) of farmer (n=554)	Spouse or child of farmer (n=854)	Household member other than spouse or child (n=1063)
Farmer						
Female farmer (dummy)	0.25 (0.43)	0.03 (0.18) †	0.02 (0.13) †	0.03 (0.17) †	0.05 (0.21) †	0.06 (0.23) †
Age (years)	47.33 (15.16)	54.55 (16.73)	53.74 (14.75)	53.34 (13.68)	52.29 (15.03)	51.55 (16.55)
Education (years)	4.49 (5.16)	3.41 (5.03)	3.48 (4.76)	3.53 (4.74)	3.65 (4.77)	3.71 (5.15)
Production						
All crops (maize kg/ha)	1280.84 (1734.43)	1106.63 (1631.81) †	1083.67 (1682.33) †	1175.88 (1666.27) †	1116.40 (1591.49) †	1167.84 (1670.62) †
Maize (Kg/ha)	2531.11 (7238.73)	2027.21 (5830.71) †	1995.92 (4806.25) †	1978.00 (4308.30) †	2110.23 (4868.93) †	2024.52 (5299.89) †
Rice (Kg/ha)	1184.07 (2038.12)	863.84 (1267.28)	923.98 (1604.56)	1338.84 (2317.48)	1244.44 (2106.55)	1090.68 (2262.27)
Millet (Kg/ha)	894.88 (1335.52)	875.54 (1486.45) †	800.78 (1376.75) †	969.96 (1661.49) †	871.59 (1409.70) †	870.92 (1538.65) †
Sorghum (Kg/ha)	883.78 (1223.74)	805.87 (1083.82) †	459.29 (416.79) †	706.28 (814.43) †	538.27 (567.26) †	904.61 (1418.84) †
Beans (Kg/ha)	947.63 (1715.62)	929.79 (2430.77)	712.66 (998.85)	931.05 (2019.80)	876.20 (1755.24)	907.22 (2070.12)
Peanut (Kg/ha)	1239.47 (2502.86)	1621.41 (3820.05) †	1105.23 (1521.65) †	873.54 (1119.79) †	937.49 (1250.23) †	1434.49 (3307.86) †
Cassava (Kg/ha)	1361.29 (2781.28)	1521.39 (3343.04) †	1495.18 (3489.49) †	1327.39 (2614.49) †	1440.15 (3031.01) †	1483.50 (3235.28) †
Yam (Kg/ha)	1634.16 (2870.58)	2437.15 (4022.65) †	1005.33 (1192.69) †	1915.05 (3405.44) †	1701.27 (2939.46) †	2085.37 (3399.75) †
Cocoyam (Kg/ha)	477.47 (1065.11)	290.26 (531.42) †	144.39 (151.63) †	-	142.62 (122.94) †	312.88 (647.24) †
Plantain (Kg/ha)	1037.24 (2061.35)	954.59 (1575.75) †	406.53 (527.37) †	1283.08 (2481.28) †	983.92 (2130.88) †	945.97 (1626.71) †
Pepper (Kg/ha)	664.36 (1470.13)	529.07 (1547.48) †	197.71 (207.93) †	586.72 (899.27) †	459.70 (808.68) †	470.80 (1259.22) †
Okra (kg/ha)	350.26 (658.73)	281.80 (656.94) †	747.68 (1737.12) †	404.80 (612.27) †	299.88 (548.64) †	458.27 (999.59) †
Tomato (kg/ha)	526.99 (1280.09)	251.54 (209.50) †	222.53 (286.37) †	1279.28 (1181.99) †	1015.09 (1117.56) †	227.28 (263.91) †
Cocoa (Kg/ha)	650.12 (1593.15)	304.16 (296.64) †	484.25 (965.14) †	581.17 (1406.04) †	550.26 (1273.61) †	329.13 (322.83) †
Palm (Kg/ha)	1139.80 (3473.80)	683.37 (1635.37) †	232.21 (366.57) †	1113.04 (2919.03) †	1093.38 (2724.20) †	518.75 (1097.67) †
Land (ha)	1.83 (2.41)	1.47 (1.82)	1.93 (2.76)	2.02 (2.79)	1.95 (2.74)	1.62 (2.27)
Land owned (dummy)	0.62 (0.49)	0.64 (0.48) †	0.63 (0.48) †	0.63 (0.48) †	0.62 (0.48) †	0.64 (0.48) †
Crop diversification (index)	0.46 (0.26)	0.46 (0.26) †	0.49 (0.25) †	0.49 (0.26) †	0.50 (0.26) †	0.49 (0.25) †
Seed (GHC/ha)	135.12 (684.10)	79.76 (253.70)	94.64 (458.64)	105.24 (333.03)	97.18 (369.78)	92.48 (327.66)
Household labor (AE)	7.17 (6.69)	6.37 (5.96) †	7.69 (6.70) †	9.17 (8.44) †	8.52 (7.92) †	8.14 (7.62) †
Hired labor (man-days/ha)	20.03 (78.85)	14.89 (52.91) †	30.93 (285.90) †	19.42 (55.32) †	23.21 (175.09) †	15.51 (53.56) †
Fertilizer (Kg/ha)	263.20 (7154.01)	132.89 (311.14) †	149.62 (358.66) †	305.08 (2194.90) †	249.41 (1769.26) †	143.81 (351.25) †
Pesticide (Liter/ha)	19.51 (295.07)	10.74 (27.77)	10.14 (21.86)	20.79 (88.14)	16.95 (71.74)	10.55 (27.39)
Mechanization (dummy)	0.05 (0.21)	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)
Irrigation (dummy)	0.02 (0.14)	0.01 (0.08) †	0.01 (0.08) †	0.04 (0.20) †	0.03 (0.18) †	0.01 (0.11) †
Credit (dummy)	0.12 (0.33)	0.09 (0.29)	0.11 (0.31)	0.13 (0.33)	0.13 (0.33)	0.10 (0.30)
Household						
Size (AE)	5.45 (3.17)	4.88 (2.83)	5.74 (2.99)	7.20 (3.30)	6.85 (3.43)	5.73 (3.26)
Dependency (ratio)	1.42 (1.70)	1.25 (1.68)	1.55 (1.84)	1.48 (1.70)	1.51 (1.76)	1.37 (1.55)

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across disability status.
The mean mid-rate interbank FX rate between the Ghana cedi (GH₵) and the US Dollar ($) for December 2019 was 5.54 GH₵/$ as reported by the Bank of Ghana
Data Sources: Ghana Living Standards Survey [waves 6-7]

Table S3. Trends in the Characteristics of Crop Producers in Ghana (2012-2017)

Variable	**Pooled (n=19862)**	**Disabled person**				
		Farmer (n=625)	**Spouse of farmer (n=313)**	**Child (adopted or biological) of farmer (n=554)**	**Spouse or child of farmer (n=854)**	**Household member other than spouse or child (n=1063)**
Farmer						
Female farmer (dummy)	-5.21*** [1.42] †	-6.94*** [2.34] †	-8.67** [3.57] †	-4.84* [2.63] †	-9.02*** [2.24] †	-3.40* [1.85] †
Age (years)	0.34 [0.44] †	0.11 [0.73] †	0.60 [0.89] †	0.31 [0.69] †	0.87 [0.59] †	-0.15 [0.61] †
Education (years)	2.48 [2.09] †	2.46 [3.91] †	0.38 [4.86] †	4.58 [3.72] †	4.45 [2.88] †	0.83 [2.87] †
Production						
All crops (maize kg/ha)	8.66*** [2.21] †	9.14** [4.44] †	9.15* [4.97] †	12.51*** [4.04] †	11.26*** [3.20] †	5.95** [2.92] †
Maize (Kg/ha)	17.60*** [5.64]	15.84 [10.90] †	15.12 [12.91] †	21.83** [8.83] †	19.64** [8.01] †	14.64** [7.37] †
Rice (Kg/ha)	21.96*** [8.03] †	19.61** [9.31] †	38.04 [25.32] †	23.91* [12.94] †	22.53** [10.79] †	20.32* [10.86] †
Millet (Kg/ha)	-1.05 [3.89] †	13.05 [8.44] †	-5.42 [8.55] †	-1.08 [6.67] †	-0.08 [5.23] †	0.13 [5.23] †
Sorghum (Kg/ha)	-5.92 [4.71] †	-1.19 [8.33] †	-3.41 [6.84] †	1.19 [6.48] †	0.12 [4.92] †	-6.51 [5.94] †
Beans (Kg/ha)	9.90 [6.59] †	34.23 [24.12] †	-5.75 [8.38] †	21.05** [10.70] †	10.50 [7.22] †	10.66 [10.13] †
Peanut (Kg/ha)	18.51*** [7.07] †	31.11* [16.70] †	-2.80 [11.60] †	12.51* [6.99] †	6.35 [5.79] †	24.11** [10.12] †
Cassava (Kg/ha)	60.65*** [19.21] †	86.37 [87.86] †	-281.42 [4381.28] †	51.29** [25.59] †	93.15 [90.01] †	47.89*** [15.36] †
Yam (Kg/ha)	172.21 [277.81] †	-12.10 [67.94] †	13.79 [14.07] †	881.97 [15259.29] †	62.55** [31.21] †	-73.01 [269.02] †
Cocoyam (Kg/ha)	41.22 [32.46] †	26.40 [34.00] †	-60.35 [73.07] †	-	-72.92 [126.41] †	31.46 [290.43] †
Plantain (Kg/ha)	52.37*** [19.81] †	36.62** [15.97] †	-2.30 [7.34] †	-317.39 [6589.83] †	122.21 [237.36] †	32.40** [13.57] †
Pepper (Kg/ha)	37.60*** [11.79]	37.28*** [13.99] †	19.09 [18.16] †	57.98 [54.64] †	52.31* [26.85] †	25.44** [11.54] †
Okra (kg/ha)	0.25 [13.87] †	-13.45 [20.48] †	538.76 [438.32] †	-22.09 [21.62] †	-3.97 [16.33] †	0.91 [19.73] †
Tomato (kg/ha)	3.54 [16.71] †	-5.04 [10.85] †	-26.84*** [0.00] †	-18.88 [14.03] †	-7.81 [18.43] †	5.83 [12.81] †
Cocoa (Kg/ha)	10.70 [8.04]	-0.26 [6.60]	25.70 [24.24]	14.10 [15.92]	18.05 [13.83]	3.34 [5.10]
Palm (Kg/ha)	-22.39 [557.88] †	293.16 [527.78] †	-32.74 [27.47] †	24.74 [212.32] †	51.51 [107.16] †	26.94 [29.60] †
Land (ha)	5.22*** [1.91] †	5.22* [2.70] †	4.01 [4.19] †	4.62 [3.40] †	5.16* [2.71] †	5.62** [2.51] †
Land owned (dummy)	3.79*** [1.05] †	1.50 [1.70] †	5.69** [2.51] †	3.75* [1.95] †	3.73** [1.60] †	3.71*** [1.30] †
Crop diversification (index)	-3.49*** [0.76] †	-4.94*** [1.42] †	-3.18* [1.75] †	-4.37*** [1.41] †	-4.43*** [1.16] †	-2.77*** [0.97] †
Seed (GHC/ha)	27.69*** [6.99]	9.00 [8.56]	87.18 [100.10]	46.53** [18.22]	48.98*** [17.78]	14.26** [6.46]
Household labor (AE)	10.86*** [1.41]	9.68*** [2.12] †	7.15** [2.97] †	10.92*** [2.55] †	10.75*** [2.13] †	10.47*** [1.76] †
Hired labor (man-days/ha)	-1.14 [8.59] †	5.65 [7.33] †	-33.10 [60.42] †	16.71* [8.55] †	0.15 [14.61] †	-1.04 [5.18] †
Fertilizer (Kg/ha)	31.11* [18.59] †	3.19 [5.18] †	26.38** [11.35] †	132.35 [447.15] †	75.90 [88.72] †	5.95 [4.14] †
Pesticide (Liter/ha)	12.40 [8.23] †	10.59* [5.93] †	15.44* [8.80] †	19.52 [18.52] †	21.78 [15.49] †	3.37 [4.16] †
Mechanization (dummy)	-12.48** [5.05] †	-15.31* [8.35] †	-25.14** [11.00] †	-9.19 [8.90] †	-12.56 [7.76] †	-12.28* [6.48] †
Irrigation (dummy)	-2.84 [11.95] †	-9.07 [23.00] †	1181.96*** [68.95] †	-14.03 [18.92] †	-0.09 [15.34] †	-2.91 [16.50] †
Credit (dummy)	5.25 [4.17] †	17.52** [7.12]	5.16 [9.75]	13.09* [6.70]	7.90 [5.54]	3.45 [6.06]
Household						
Size (AE)	-0.84 [0.83] †	0.55 [1.43] †	-0.36 [1.66] †	-1.42 [1.18] †	-0.74 [1.13] †	-0.55 [1.11] †
Dependency (ratio)	3.17* [1.85]	2.47 [4.05] †	4.38 [4.38] †	3.62 [3.00] †	3.68 [2.64] †	1.74 [2.46] †

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across disability status.
The mean mid-rate interbank FX rate between the Ghana cedi (GH₵) and the US Dollar ($) for December 2019 was 5.54 GH₵/$ as reported by the Bank of Ghana
Data Sources: Ghana Living Standards Survey [waves 6-7]

Table S4. Meta Stochastic Frontier Analysis Results for Ghanaian Crop Producers for the periods 2012/13 and 2016/17

	Naïve national frontier	Group frontier		Meta-frontier	
		Not disabled	Disabled	Matched	Unmatched
Production function					
Land [lnI1]	0.693*** (0.001)	0.695*** (0.001)	0.682*** (0.001)	0.680*** (0.003)	0.694*** (0.001)
Planting material [lnI2]	0.059*** (0.000)	0.059*** (0.000)	0.064*** (0.000)	0.059*** (0.000)	0.059*** (0.000)
Family labor [lnI3]	0.168*** (0.000)	0.169*** (0.000)	0.119*** (0.004)	0.171*** (0.001)	0.169*** (0.001)
Hired labor [lnI4]	0.027*** (0.000)	0.027*** (0.000)	0.028*** (0.000)	0.027*** (0.000)	0.027*** (0.000)
Fertilizer [lnI5]	0.029*** (0.000)	0.028*** (0.000)	0.031*** (0.000)	0.029*** (0.000)	0.028*** (0.000)
Pesticide [lnI6]	0.019*** (0.000)	0.018*** (0.000)	0.031*** (0.000)	0.021*** (0.001)	0.019*** (0.000)
1/2 * lnI1 * lnI1	0.107*** (0.000)	0.108*** (0.000)	0.095*** (0.001)	0.107*** (0.001)	0.107*** (0.000)
lnI1*lnI2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000*** (0.000)
lnI1*lnI3	-0.058*** (0.000)	-0.058*** (0.000)	-0.065*** (0.000)	-0.059*** (0.000)	-0.058*** (0.000)
lnI1*lnI4	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
lnI1*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)
lnI1*lnI5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001*** (0.000)	0.000*** (0.000)
1/2 * lnI2 * lnI2	0.005*** (0.000)	0.005*** (0.000)	0.006*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
lnI2*lnI3	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)
lnI2*lnI4	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
lnI2*lnI6	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
lnI2*lnI5	0.000** (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
1/2 * lnI3 * lnI3	0.019*** (0.000)	0.019*** (0.000)	0.057*** (0.002)	0.023*** (0.001)	0.020*** (0.000)
lnI3*lnI4	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
lnI3*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)
lnI3*lnI5	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.001*** (0.000)	0.000 (0.000)
1/2 * lnI4 * lnI4	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
lnI4*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000*** (0.000)
lnI4*lnI5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
1/2 * lnI5 * lnI5	0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
lnI5*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
1/2 * lnI6 * lnI6	0.003*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Proportion of area under listed crop (base=maize)					
Cassava	-0.598*** (0.013)	-0.604*** (0.010)	-0.512*** (0.020)	-0.585*** (0.013)	-0.600*** (0.010)
Peanut	0.237*** (0.004)	0.224*** (0.003)	0.344*** (0.006)	0.241*** (0.006)	0.232*** (0.003)
Plantain	-0.420*** (0.017)	-0.426*** (0.012)	-0.325*** (0.028)	-0.418*** (0.012)	-0.423*** (0.012)
Rice	-0.048*** (0.002)	-0.036*** (0.002)	-0.144*** (0.005)	-0.037*** (0.002)	-0.039*** (0.002)
Millet	-0.179*** (0.004)	-0.184*** (0.004)	-0.164*** (0.007)	-0.161*** (0.007)	-0.180*** (0.004)
Sorghum	-0.275*** (0.002)	-0.268*** (0.002)	-0.300*** (0.005)	-0.260*** (0.004)	-0.269*** (0.002)
Beans	-0.201*** (0.005)	-0.185*** (0.005)	-0.347*** (0.005)	-0.182*** (0.006)	-0.187*** (0.005)
Yam	-0.058*** (0.007)	-0.058*** (0.006)	-0.080*** (0.018)	-0.051*** (0.006)	-0.059*** (0.006)
Cocoa	1.229*** (0.002)	1.226*** (0.002)	1.285*** (0.006)	1.235*** (0.008)	1.228*** (0.002)
Other	-0.344*** (0.014)	-0.301*** (0.011)	-0.692*** (0.014)	-0.309*** (0.016)	-0.309*** (0.013)
Ecological zone [base = Coastal Savanna]					
Forest	0.143*** (0.005)	0.147*** (0.005)	0.051*** (0.019)	0.141*** (0.016)	0.146*** (0.006)
Guinea Savanah	-0.735*** (0.059)	-0.742*** (0.045)	-0.850*** (0.046)	-0.758*** (0.033)	-0.749*** (0.045)
Sudan Savanah	-0.750*** (0.059)	-0.746*** (0.045)	-0.898*** (0.045)	-0.763*** (0.033)	-0.751*** (0.045)
Transitional	0.019*** (0.005)	0.009* (0.005)	0.070*** (0.011)	0.091*** (0.018)	0.014*** (0.005)
Period (base=2012/13)					
2016/17	0.152*** (0.023)	0.156*** (0.017)	0.058*** (0.020)	0.158*** (0.018)	0.156*** (0.018)
Intercept	6.711*** (0.049)	6.726*** (0.037)	6.731*** (0.038)	6.785*** (0.027)	6.756*** (0.037)
Production risk function					
Intercept	-0.335*** (0.018)	-0.342*** (0.014)	-0.398*** (0.016)	-9.094 (5.763)	-8.301*** (0.377)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).

Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample.

Table A5. Determinants Of Crop Production Technical Inefficiency and Disability Driven Technology Gaps in Ghana (2012-2017)

	Naïve national frontier	Group frontier		Meta-frontier	
		Not disabled	Disabled	Matched	Unmatched
Female farmer (dummy)	0.318*** (0.009)	0.327*** (0.009)	0.203*** (0.011)	0.040*** (0.009)	0.292*** (0.012)
Age (years)	0.252*** (0.004)	0.239*** (0.005)	0.289*** (0.012)	0.229*** (0.018)	0.626*** (0.022)
Education (years)	0.008*** (0.000)	0.008*** (0.000)	0.013*** (0.003)	0.002 (0.002)	-0.005*** (0.002)
Land owned (dummy)	-0.001 (0.007)	-0.003 (0.005)	0.060*** (0.014)	-0.204*** (0.016)	-0.168*** (0.016)
Crop diversification (index)	0.296*** (0.031)	0.258*** (0.033)	0.548*** (0.064)	0.489*** (0.029)	0.677*** (0.030)
Mechanization (dummy)	-0.825*** (0.042)	-0.788*** (0.041)	-26.731*** (3.888)	0.138*** (0.016)	0.170*** (0.010)
Credit (dummy)	0.148*** (0.006)	0.174*** (0.005)	-0.149*** (0.010)	0.007 (0.009)	-0.099*** (0.024)
Extension (dummy)	-0.108*** (0.029)	-0.107*** (0.020)	-0.095* (0.054)	-0.114*** (0.006)	-0.181*** (0.008)
Ecological zone [base = Coastal Savanna]					
Forest	0.261*** (0.010)	0.248*** (0.012)	0.250*** (0.054)	0.505*** (0.187)	0.335 (0.717)
Guinea Savanah	-37.791*** (5.252)	-37.620*** (4.785)	-31.959*** (0.995)	0.275 (0.242)	-0.122 (0.290)
Sudan Savanah	-40.181*** (0.187)	-39.872*** (0.182)	-36.759*** (0.122)	0.491* (0.254)	0.535* (0.309)
Transitional	0.114*** (0.016)	0.070*** (0.015)	0.427*** (0.020)	0.441*** (0.151)	-0.479*** (0.133)
Period (base=2012/13)					
2016/17	-1.868 (9.154)	-1.832 (6.486)	-1.715 (7.712)	0.745*** (0.105)	0.573*** (0.118)
Intercept	-0.938*** (0.133)	-0.826*** (0.112)	-1.320*** (0.074)	-5.132*** (0.234)	-8.396*** (0.160)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

[a] Null hypothesis of no one-sided error (i.e., no inefficiency) was tested.

Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).

Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample.

Figure S1. Covariate balancing summary

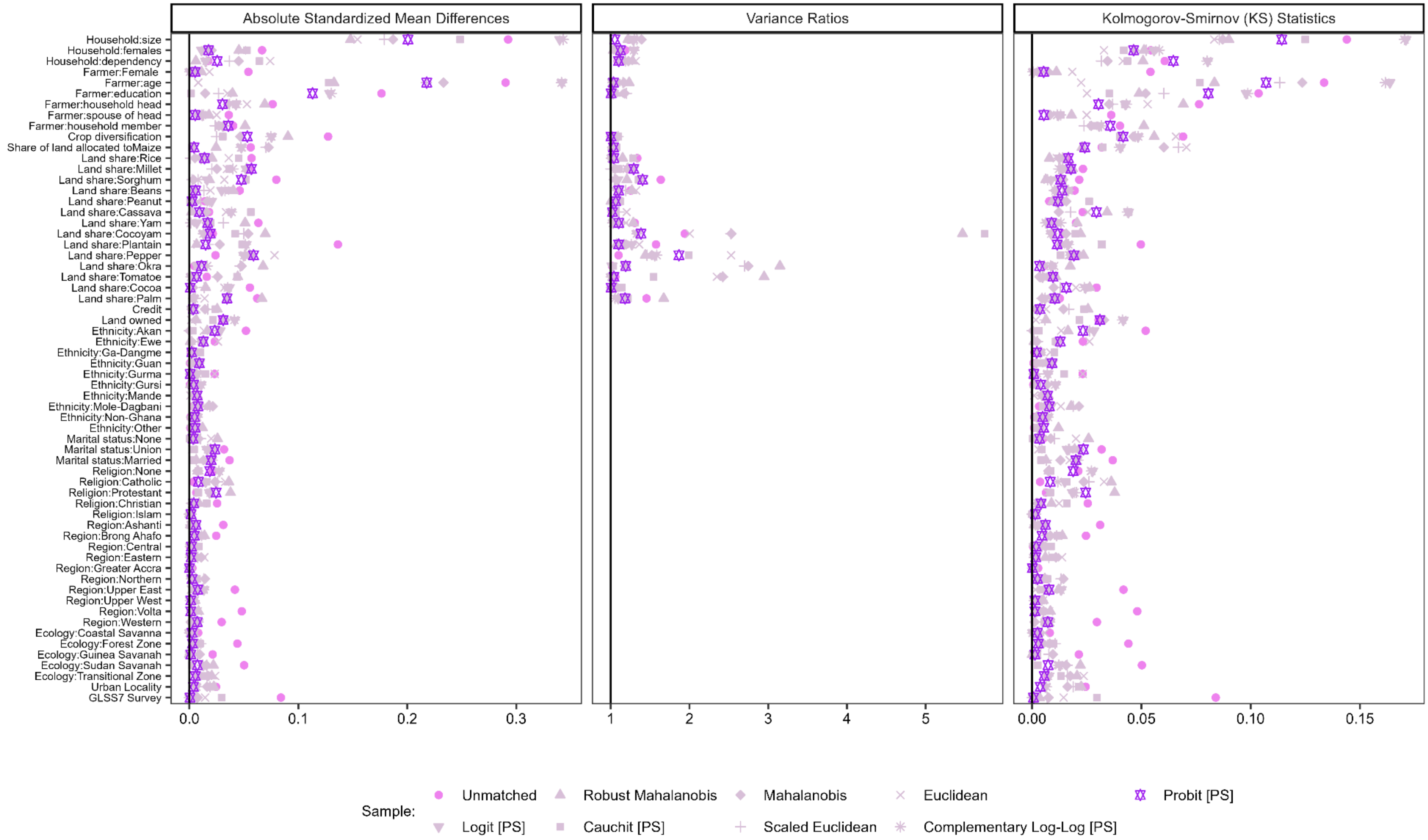
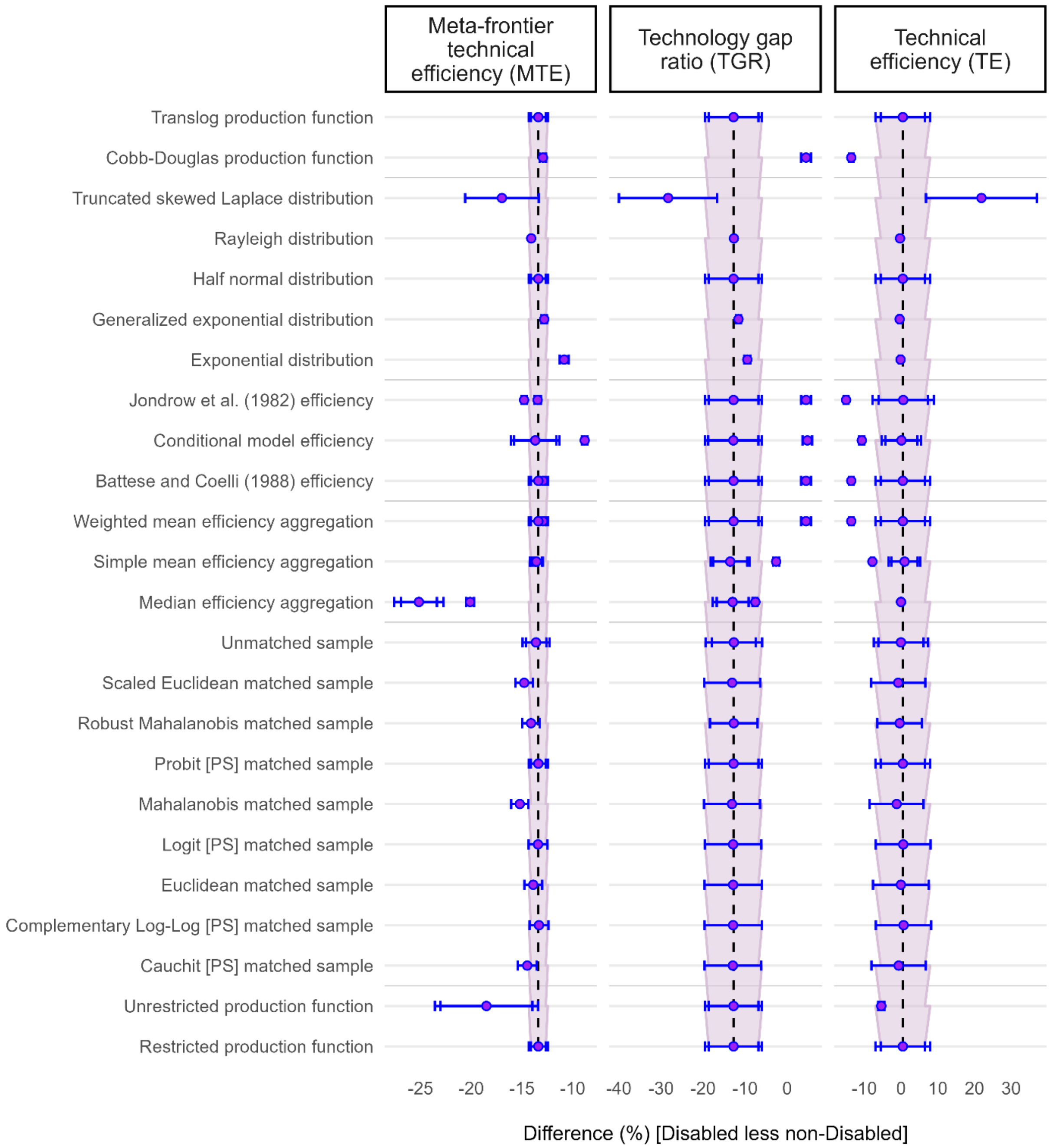


Figure S2. Different Model Specification Generally Show Decreasing Impact of Farmer Disability on Crop Production Output for Ghanaian Farmers (2012-2017)



Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]). Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample.