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Social networks, adoption of improved variety and household welfare: evidence from Ghana

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Abstract

In this study, we examine the effects of own and peer adoption of improved soybean variety on household yields and food and nutrient consumption, using observational data from Ghana. We employ the marginal treatment effect approach to account for treatment effect heterogeneity across households and a number of identification strategies to capture social network effects. Our empirical results show that households with higher unobserved gains are more likely to adopt because of their worse outcomes when not adopting. We also find strong peer adoption effect on own yield, only when the household is also adopting, and on food and nutrient consumption when not adopting. However, the peer adoption effect on consumption attenuates when the household adopts the improved variety. Furthermore, our findings reveal that adoption tends to equalise households in terms of observed and unobserved gains on consumption and can thus serve as a mechanism for promoting food security and nutrition in this area.

Keywords: improved variety, technology adoption, social networks, marginal treatment effects, food and nutrition security

JEL classification: C21, D60, D85, O13, O33

1. Introduction

Food insecurity remains a major concern across many sub-Saharan African countries, despite significant strides and improvements in agricultural technologies and crop varieties over the past few decades (Shiferaw *et al.*, 2014; Food and Agriculture Organization (FAO) *et al.*, 2019). Globally, the prevalence of hunger increased from 10.6 per cent in 2015 to 10.8 per cent in 2018, while that of sub-Saharan Africa increased from 20.9 per cent in 2015 to 22.8 per cent in 2018 (FAO *et al.*, 2019), suggesting the prevalence in sub-Saharan Africa is not only twice that of the world prevalence but also a cumulative increase from 2015 of about nine times that of the

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world. This increasing food insecurity in the midst of increased availability of improved agricultural technologies, particularly in sub-Saharan Africa (Minten and Barrett, 2008; Shiferaw *et al.*, 2014), suggests the need to obtain a better understanding of technology adoption and consumption of food and specific nutrients in order to enhance the effectiveness of improved technologies in addressing food insecurity in these areas.

While the literature has made significant strides in investigating the importance of improved crop varieties on household welfare, not much consideration has been given to the impact of improved crop varietal adoption by households and their peers on household food and nutrient consumption (Minten and Barrett, 2008; Shiferaw *et al.*, 2014; Smale, Moursi and Birol, 2015; Verkaart *et al.*, 2017). Also, studies that examined the impact of technology adoption on performance outcomes tend to focus on crop yield and income-related measures (e.g. Becerril and Abdulai, 2010; Abdulai and Huffman, 2014; Verkaart *et al.*, 2017; Wossen *et al.*, 2019). There is virtually no rigorous empirical evidence on the potential impact of improved crop varieties on the consumption of specific nutrient-rich foods among households (Hotz *et al.*, 2012; Smale, Moursi and Birol, 2015; Larsen and Lilleør, 2016; Ogutu *et al.*, 2020).[1] The few that examined the impact of improved crop varietal adoption on food security and nutrition focused on food group diversity and vitamin A intake (Hotz *et al.*, 2012; Smale, Moursi and Birol, 2015; Larsen and Lilleør, 2016), without much consideration given to the other components of nutrients such as protein-rich food intake. In particular, improving household consumption of protein-rich foods is important in the prevention of wasting, stunting and micronutrient deficiencies that cause diseases and deaths.[2] Thus, a better understanding of the link between adoption of improved technology and consumption of food and these specific nutrients is key in helping policymakers design policies to promote food and nutrition security.

Despite the increasing interest in understanding the role of social interaction on households' decision-making and individual welfare (e.g. Bandiera and Rasul, 2006; Fafchamps and Gubert, 2007; Conley and Udry, 2010; Garcia, Kere and Stenger, 2014; De Giorgi, Frederiksen and Pistaferri, 2020), the voluminous literature on social interactions has virtually not provided evidence on the potential benefits of peer adoption of agricultural technologies on household food and nutrient consumption. With the exception of a few such as Maurer and Meier (2008) and De Giorgi, Frederiksen and Pistaferri (2020) on endogenous consumption peer effects and Kuhn *et al.* (2011) on lottery prices,[3] this has not been done on peer adoption effects. There are various reasons one

1 Previous studies focused on production diversification on households' and children's dietary diversity and consumption of specific food groups (Dillon, McGee and Oseni, 2015; Lovo and Veronesi, 2019); caregivers' nutrition knowledge on the types of foods consumed by children (Hirvonen *et al.*, 2017) and the impacts of improved extension designs on smallholder sensitivity to nutrition (Ogutu *et al.*, 2020). See Sibhatu and Qaim (2018) for a meta-analysis.

2 WFP (2015) argues that tackling vitamin A deficiency, before the age of 5, can reduce mortality and infectious diseases up to a third.

3 Maurer and Meier (2008) study intertemporal consumption effects among peers using panel data from the USA and find moderate but significant evidence of consumption externalities across peer groups. De Giorgi, Frederiksen and Pistaferri (2020) investigate consumption network effects,

will expect spillovers from peer adoption on household food and nutrient consumption. First, peer adoption that leads to increased learning opportunities and productivity of the household can enhance the household's consumption, especially in rural Africa, where the issues of missing and inefficient markets are prevalent (de Janvry, Fafchamps and Sadoulet, 1991). Second, when peer adoption of the improved variety leads to increased peer productivity, and changes in peer consumption, this can affect household's own consumption either due to the endogenous peer effect, or through private cash transfers to the household in a form of safety net.

The purpose of this study is twofold: to investigate the effect of household adoption of improved crop variety on the consumption of food and specific nutrients among households and to examine the effect of peer adoption of the improved crop variety on yield and food and nutrient consumption. We do this by using detailed data of 500 farm households from northern Ghana to examine the effect of household and peer adoption of improved soybean variety on crop yield and the household's consumption of food and vitamin-A- and protein-rich foods. Analytically, we exploit spatial econometric techniques to generate instruments (Bramoullé, Djebbari and Fortin, 2009; Acemoglu, Garci-Jimeno and Robinson, 2015) and then use the instruments, in addition to controlling for network fixed effects and potential endogeneity of network link formation with the control function approach by Brock and Durlauf (2001), to identify peer adoption effects on own adoption and outcomes. We employ the marginal treatment effects (MTEs) approach, following Heckman and Vytlacil (2005) and Cornelissen *et al*. (2018), to estimate the treatment effect heterogeneities. This approach is significant in the sense that it allows us to identify, at least, a substantial part of the range of individual treatment effects and as a result characterise the extent and pattern of treatment effect heterogeneity (Cornelissen *et al.*, 2016, 2018).[4]

Poverty incidence and its extreme form have been consistently higher in northern Ghana than the national average and that of the rest of the country since 2005, and with worsening rates of extreme poverty, as the incidence increased from 29.7 per cent in 2012/2013 to 34.5 per cent in 2016/2017 (Ghana Statistical Service (GSS), 2018). This has resulted in higher incidence of food insecurity and malnutrition in the area, compared to the rest of the country, and the use of a number of strategies including credit purchases and borrowing from friends and relatives to cope with food insecurity (World Food Program (WFP) and GSS, 2012). This makes northern Ghana a suitable area

using administrative data set and complementing it with data on consumption survey of households' expenditure on goods, and find peer consumption effects on household consumption to be non-negligible. Kuhn *et al.* (2011) study the effect of lottery prices on neighbours of winners and find evidence for effects of lottery prices on winners' neighbours, but only for consumption of cars.

4 Previous studies (e.g. Minten and Barrett, 2008; Shiferaw *et al.*, 2014) have assumed homogenous treatment effects, focusing mainly on addressing selectivity problems arising from unobserved characteristics, and aggregate parameter estimates. As argued by Cornelissen *et al.* (2016), this approach can mask important heterogeneity in treatment effects.

for assessing the impact of improved crop varietal adoption by households and their peers on crop yield and household food and nutrient consumption.

Our findings show strong evidence of heterogeneity in returns to adoption in both observed and unobserved characteristics. Specifically, we find positive selection on gains due to unobserved characteristics, mainly driven by worse outcomes, of households with less resistance to adopt, in the non-adoption state. However, adoption appears to make the potential outcomes of households quite homogenous, irrespective of their level of resistance to adoption. Peer adoption increases the household's food and nutrient consumption, when the household is not adopting the improved variety, but with attenuating effects when the household adopts, suggesting that non-adopters tend to depend more on adopting peers in terms of food and nutrient consumption than adopters. We, however, note that the estimated effects cannot be interpreted as causal effects in its strictest sense, given that households were not randomly assigned to treatment and control groups, as in a randomised controlled trial.[5]

Our study contributes to the literature in threefold: first, it provides empirical insights into the importance of improved crop varieties on welfare indicators such as crop yields and consumption of specific nutrient-rich foods, while highlighting heterogeneity in returns to adoption in observed and unobserved characteristics. To the best of our knowledge, this is the first study to use this approach to quantify the effects of improved crop variety on food and nutrient consumption. Second, the paper presents evidence of exogenous interaction effects (Manski, 2013) on food and nutrient consumption of smallholders. As indicated previously, understanding the relationship between peer adoption and household consumption may present an alternative to public food and nutrition security interventions through private transfers among peers, given the challenges of sustainable and exit mechanisms of public food transfer modalities (Holden, Barrett and Hagos, 2006). Finally, the study provides insights into the effectiveness of policy options (i.e. whether to promote affordability or availability of the improved soybean seeds) that shift some non-adopting households to adopt on the outcomes.

The next section presents the conceptual framework of the analysis. In Section 3, we present the context and data used in the analysis. Section 4 presents the analytical and empirical frameworks and estimation. In Section 5, we report the results and then discuss in Section 6. The final section presents a brief summary and conclusions.

2. Conceptual framework

In this section, we explore the conceptual mechanisms by which own and peer adoption may affect crop yield and food and nutrient consumption. To the extent that the improved variety is characterised as high yielding, early maturing and resistant to agricultural and climatic stress (Council for Scientific and Industrial Research-Savanna Agricultural Research Institute (CSIR-SARI),

5 We thank the reviewers and editor for suggesting this to us.

2013), own adoption of the improved variety can lead to increased yields and reduced production costs, which may result in increased farm income and subsequently increased food consumption. However, when own adoption and investments in the new variety is not complemented with good production 'know-how', or soybean market, this may lead to reduced income and food consumption, since soybean is not a staple food in the area but is mainly produced for cash sales.[6] Similarly, food and nutrient consumption may decrease, if additional income from adoption of the improved variety is not spent on food and nutrients (Carletto *et al.*, 2015; Sibhatu and Qaim, 2018).

Given that smallholder farmers in the rural areas of developing countries often face missing or inefficient markets, making household production and consumption decisions jointly determined and thus 'non-separable' (de Janvry, Fafchamps and Sadoulet, 1991), peer adoption decisions that affect household production can alter household consumption decisions as well. For example, peer adoption that provides learning opportunities and eases input constraints can lead to increased crop yield, farm income and consequently food consumption possibilities (Conley and Udry, 2010; De Giorgi, Frederiksen and Pistaferri, 2020). However, when a household does not adopt, peer adoption can reduce (increase) learning opportunities (costs), especially if the production processes of the improved and traditional varieties are not complementary (Niehaus, 2011), which can constrain household productivity, income and possibly consumption capabilities.

Peer adoption effects can also impact on own yield and food consumption through private transfers that result in a shift in the household's resources. In particular, if peer adoption leads to increased yield, income and wealth of peers, this can as well empower peers to undertake private transfers to the household. This can then lead to an increase in the household resource possibilities to (i) directly spend on food and/or (ii) indirectly relax the liquidity constraint of the household in production, which may increase crop yield and food consumption possibilities. However, own adoption by the household, which leads to increased productivity and income especially of poorer households, may attenuate peer effects through private transfers on the households' food consumption, when the increase in productivity and income from adoption leads to a decrease in the private transfers from peers or reduce dependence on peers. Studies have noted that when the cost of sharing or altruistic effort is sufficiently higher than the benefit, no member will undertake any effort to share (e.g. Alger and Weibull, 2012; Di Falco and Bulte, 2013). Finally, peer adoption effect on food consumption could decline, following own adoption,

6 The other pathways through which agriculture production can affect food security and nutrition are changes in food prices, consumption of own production and intra-household dynamics related to gender and resource control. However, we do not emphasise the food price and intra-household effects because the focus of the study is on farm-level effects and not on individual household members (Carletto *et al.*, 2015). Also, consumption of own production is not emphasised here because soybean is not a staple food in the study area but a crop that is mainly produced for cash sales and incomes (CSIR-SARI, 2013).

if own adoption by the household leads to increased productivity and results in the need to settle past transfer commitments (Di Falco *et al.*, 2018).

We deduce a number of implications from the foregoing discussion to guide our interpretation of the empirical results. When the household is not adopting, the impact of peer adoption on the household's yield and food consumption could be either positive, if the production processes of the improved and traditional varieties are complementary, or negative if otherwise, thereby constraining transferability of production 'know-how' and other inputs. The impact of peer adoption on household food security should be positive, if peer adoption leads to increased private transfers from peers. When the household adopts, the impact of peer adoption on crop yield and food consumption could be positive if own adoption enhances learning and relaxes input constraints, which leads to increased household productivity, income and spending on food. On the contrary, the impact of peer adoption on consumption in particular could be negative, if increased productivity and income due to own adoption either results in reduction of dependence on social transfers from peers or in the need to return private transfers received from peers by the household, indicating peer and own adoption are substitutes (Di Falco *et al.*, 2018).

3. Context and data

3.1. Context

Ghana is a lower middle-income country that has made steady progress in economic growth and food security and in reducing poverty rate from 56.5 per cent in 1991 to 23.4 per cent in 2018 (GSS, 2018). Despite this progress, substantial regional disparities exist, with some of the poorest indicators (i.e. high incidence of poverty, food insecurity and malnutrition) found in the northern part of the country. In the three northern regions (Northern, Upper East and Upper West regions) of Ghana, about 16 per cent of all households are food insecure, with diets consisting of staple foods and occasionally accompanied by oil and vegetables (WFP and GSS, 2012). Food insecurity in these regions is largely associated with poverty, weather constraints, seasonal effects and high food prices. The major sources of food for households are own production and market purchases, with more than 65 per cent of food consumption coming from cash purchases during the lean season months. Similarly, households in this area resort to borrowing food or money from friends and relatives in coping with food insecurity (WFP and GSS, 2012).

Soybean is a viable crop that can enhance the incomes and resilience of the poor households, because of its commercial potential and also the fact that it is mainly produced in the northern regions, which are the poorest regions in the country. The climatic conditions in this area are suitable for soybean cultivation, because of the high temperature requirement of 20–30°C for successful cultivation. Among the regions of the north, the Northern region, in particular, which is the study region, accounts for over 65 per cent of the total area cultivated to the crop and produces about 72 per cent of the national output.

The crop is cultivated mostly by smallholder farmers under rain-fed conditions, with an average area cultivated of less than two acres. It has received significant promotion by the Ministry of Food and Agriculture (MoFA) and the Ghana ADVANCE[7] programme in value chain enhancement and through seed price subsidies to farmers aimed at increasing productivity and incomes (MoFA, 2017).

CSIR and SARI developed and introduced the improved variety in order to circumvent the problems associated with the traditional variety.[8] The improved variety has higher yield potential of over 2.0 MT/ha, has resistance to pod shattering, matures in about 35 days earlier and is resistant to other agricultural and climatic variabilities (CSIR-SARI, 2013). Despite these interventions, the average national yield of 1.68MT/ha has remained below the national achievable yields of 2.50–3.10MT/ha (CSIR-SARI, 2013). Also, available evidence shows that the use of improved soybean seed is still quite low, with estimates ranging between 16 and 33 per cent (CSIR-SARI, 2013) of soybean farmers. Although SARI and MoFA have worked with private seed companies and other local input dealers to enhance supply at the district level, farmers in some communities still travel long distances to acquire the seeds from input dealers (MoFA, 2017).

3.2. Data

3.2.1. Data on farm households

We conducted a survey in 25 villages across five districts in the Northern region of Ghana between June and September 2017. A random sample of 500 farm households was drawn in three stages. In the first step, we purposively sampled five soybean-producing districts in the region, based on their intensity of soybean production. In the second stage, we used a list of soybean-producing villages in each district obtained from MoFA offices to randomly sample eight villages in Savelugu-Nanton, six in Gushegu, five in Tolon, four in Karaga and two in Kumbungu districts, in proportion to the number of households engaged in agriculture in each district (GSS, 2014).

In the third stage (i.e. the village level), we conducted a listing of households in each village and randomly selected 20 households in each village for interview and a structured questionnaire was administered to them. We obtained information from households about their agricultural production for the 2016 cropping year; household land, assets and wealth; 7-day recall of daily food and nutrient consumption; and distance to the nearest soybean seed source among others. Finally, we organised a focus group discussion with 4–6 village leaders in each village, and village-level information such as local farm

7 ADVANCE refers to the Feed the Future Ghana Agricultural Development and Value Chain Enhancement Project funded by the United States Agency for International Development.

8 The traditional variety, Salintuya, has been described as low yielding (about 1.0 MT/ha). It is also known for early shattering of pods and is susceptible to disease and pests, which sometimes lead to complete loss of output (CSIR-SARI, 2013).

input prices; wage rate; and distance to the nearest paved road, market and the district capital was collected from this medium.

3.2.2. Data on social networks

We used the random matching within sample, which involves drawing a random sample from a population and collecting information on the links among them (Conley and Udry, 2010). This approach offers the advantage of having both households (i.e. nodes[9]) in any link randomly selected (Fafchamps and Gubert, 2007). At the beginning of the interview for each household, we randomly matched five households from the rest of the village sample to the household, and information was collected on the matched households the respondent knew. In particular, we collected information on exchanges of agricultural information, labour, credit and land; social relations (i.e. whether relatives and friends); and geographic proximity (i.e. whether farm neighbours) between the household and the assigned matches the household knew.

We then define the matched households the household shared any of the above exchanges, social relation and geographical proximity with as the social contacts. Using these social contacts and denoting the responding household as i and a given village as v, we next construct a 20×20 village social network, which we denote as $N(v)$. Thus, $N(v)$ denotes a symmetric matrix of the set of 20 households randomly sampled in a village, with undirected entries being equal to one if the respondent has any of these social contacts with a known match (which defines the peers) and zero if otherwise. A household in the network [i.e. $N_i(v)$][10] has an average of four links (i.e. degree) with other sampled households in the village and an average node transitivity of 0.46, suggesting that 46 per cent of triads of a household head and the peers have links with one another.

3.2.3. Descriptive statistics

This section describes the data used by focusing on the main outcomes, which are soybean yields, food consumption score (food) and nutrient-rich food consumption scores. Soybean yield is measured as the total soybean output in kilograms divided by the acres[11] cultivated to the crop by household. Given that the food and nutrient outcomes measure the frequency of consumption of food and nutrient-rich foods, we ask households the question ‘How many days in the last 7 days your household ate the following foods?’ We calculated the food consumption score by first grouping all food items consumed by households into main staple, pulses, vegetables, fruit, meat and fish, milk, sugar, oils and condiments and the food consumption score-nutrition by grouping food items into 15 food groups. We then categorised these groups into

9 **Nodes** represent agents (i.e. households in this study) in a network. **Degree** is the number of links of a household (i.e. node) in an undirected network (Chandrasekhar and Lewis, 2016).

10 $N_i(v)$ is the ith row of the network matrix $N(v)$.

11 The acres cultivated to soybean exclude the proportion of the plots cultivated to vegetables by the 1 per cent of farmers who planted some vegetables on their soybean plots.

Table 1. Descriptive statistics of outcomes by own and quintiles of average peer adoption

		By quintiles of average peer adoption				
	All	First	Second	Third	Fourth	Fifth
Main outcomes						
Soybean yield	630.7	551.8	621.8	610.9	667.9	701.1
Adopters	725.8	688.5	727.7	705.1	751.7	739.8
Non-adopters	439.5	420.5	433.7	443.5	472.3	442.3
Adopters − non-adopters	286.3***					
Food	33.6	29.5	33.2	32.4	35.2	37.3
Adopters	34.9	34.1	33.6	33.0	36.2	37.2
Non-adopters	30.7	25.1	32.6	32.0	33.1	38.6
Adopters − non-adopters	4.2***					
Vitamin A	12.4	10.1	12.4	12.0	13.5	14.3
Adopters	13.4	12.9	12.9	12.4	13.9	14.3
Non-adopters	10.5	7.3	11.5	11.0	12.4	14.4
Adopters − non-adopters	2.9***					
Protein	6.2	4.5	6.3	5.8	6.8	7.2
Adopters	7.4	7.7	7.4	6.7	7.6	7.5
Non-adopters	3.8	2.2	4.4	4.1	4.9	5.2
Adopters − non-adopters	3.8***					
Nadoption at means	0.69	0.38	0.61	0.71	0.81	0.94

Notes: The table presents means of the main outcomes and proportion of adopting peer for the sample and by quintiles of proportions of adopting peers. For each variable, the table presents the mean for all the sample, adopters and non-adopters. Nadoption denotes the proportion of peers who adopted the improved variety. The table also presents the differences between adopters and non-adopters for all the variables. *** denotes significance at 1 per cent.

vitamin-A-rich foods as dairy, organ meat, eggs, orange and green vegetables and orange fruits and protein-rich foods as pulses, dairy, flesh meat, organ meat, fish and eggs (WFP, 2015). We next sum all the consumption frequencies of the food and nutrient-rich food items of the same group. For the food consumption score, we multiply the value obtained for each food group by the group weight to obtain weighted food group scores and then add the weighted food groups to generate the food consumption score for a household.[12] For each nutrient-rich food group, we sum the number of days the food sub-group belonging to this was consumed to obtain the food consumption score-nutrition for the household (WFP, 2015).

The descriptive statistics of these outcome variables are presented in Table 1 for the whole sample and by own adoption status and quintiles of average peer

12 The food consumption score (FCS) is highly correlated with the household dietary diversity score (HDDS) given that they both measure the frequency of consumption of different food groups at the household level (FAO, 2010). However, whereas the FCS weights the various food groups based on nutrient quality, the HDDS uses the unweighted food groups in the computation. The limitation of these measures is that they do not provide information on food consumption, dietary diversity and specific nutrient intake of individuals in the household, which make them suitable only for household-level analysis (FAO, 2010; WFP, 2015).

adoption. With a mean soybean yield of 631 kg/ac, the mean yield for adopters is 726 kg/ac, which is significantly higher than the mean yield, 439 kg/ac, of non-adopters. The mean food consumption frequency is 34 for the entire sample, with the mean consumption of 35 for adopters being significantly higher than the mean food consumption of 31 for non-adopters. Similarly, adopters of the improved variety have significantly higher consumption frequencies of nutrient-rich foods (i.e. vitamin-A- and protein-rich foods). These observations motivate the empirical investigation, where there is significant unequal consumption frequencies of food and nutrient-rich foods that appear to coincide with adoption status.

Given the association between household adoption and food and nutrient consumption frequencies, we next explore whether peer adoption can possibly be associated with household food and nutrient consumption by providing descriptive statistics according to quintiles of peer adoption. The mean soybean yield increases from 552, 689 and 421 kg/ac for the lowest quintile to 701, 740 and 442 kg/ac for all the sample, adopters and non-adopters, respectively, in the top quintile—an increase that is statistically significant for all sample ($p = 0.000$) and only adopters ($p = 0.015$). The mean food consumption frequency also increases from 30, 34 and 25 for the bottom quintile to 37, 37 and 39 for the top one for the entire sample, adopters and non-adopters, respectively—an increase which is statistically significant ($p = 0.000$). However, the food consumption difference between adopters and non-adopters markedly narrows at the top quintile of peer adoption ($p = 0.449$).

Similarly, the mean consumption frequencies of nutrient-rich foods closely follow that of food consumption in general. While the consumption of vitamin-A- and protein-rich foods by non-adopters significantly increase from 7.3 and 2.2 for the bottom quintile to 14.4 and 5.2 for the top one, respectively, the consumption frequencies of adopters do not witness significant changes. The weaker correlation between peer adoption and yield of non-adopters and the stronger association between peer adoption and non-adopters' food and nutrient consumption suggest the possibility of stronger peer adoption effects in the form of risks sharing and private transfers when the farmer is not adopting.

We present definition, measurement and descriptive statistics of characteristics of the sample and peers in Table 2. Of particular interest is panel B, which presents the main instrument—distance to the nearest soybean seed source used to identify household adoption of the improved variety. In our sample, the average distance from the household location to the nearest seed source is about 6 km. Even though some households are located less than 2 km to the nearest soybean seed source, the distance increases to an average of about 11 km for the households in the highest distance quintile in the sample (see Table A1 in Appendix A3). Panel C of Table 2 shows that a household has an average of 65 per cent of the peers being males, aged 44 years and with landholding of 2.7 hectares. Also, 63 per cent of a household's peers of peers are males, aged 44 years and with landholding of 2.7 hectares (panel D).

4. Methodology

4.1. Analytical framework

The significant differences between the outcomes of adopters and non-adopters and the heterogeneity in these outcomes across the distribution of adopting peers, shown in Section 3, suggest the need for a framework that can estimate the effects of own adoption on these outcomes, while accounting for heterogeneity in gains from peer adoption, as well as other observed and unobserved characteristics of these farm households. Thus, we use the MTEs framework, which is based on the generalised Roy model (Heckman and Vytlacil, 2005; Cornelissen *et al.*, 2016, 2018).

We assume that treatment (adoption) of a household, i, is a binary variable denoted by A_i and the household's potential outcome (e.g. yield and food and nutrient consumption) under the hypothetical situation of being an adopter ($A_i = 1$) and non-adopter ($A_i = 0$) is Y_{1i} and Y_{0i}, respectively. Let A_j represent peer adoption, with ρ_1 and ρ_0 as the parameter estimates showing the effects of peer (j's) adoption on own (i) potential outcomes under the situation of the household adopting and not adopting, respectively. Also, let X_i denote a vector of farmer and household characteristics, with η_1 and η_0 being the associated vectors of parameter estimates under the situation of being an adopter and non-adopter, respectively; G_i represents a vector of village characteristics and network fixed effects. Given these definitions, we model the potential outcomes as

$$
\begin{aligned}
Y_{1i} &= \rho_1(A_j) + \eta_1\left(X_i\right) + G_i^{'}\tau + U_{1i}, \\
Y_{0i} &= \rho_0(A_j) + \eta_0\left(X_i\right) + G_i^{'}\tau + U_{0i}
\end{aligned} \tag{1}
$$

where τ is a vector of parameters to be estimated, while U_{1i} and U_{0i} represent deviations from the mean and are assumed to have means of zero. The peer adoption variable, A_j, is obtained by multiplying the adoption variable, A_i, by the$i$th row of the social network matrix $N(v)$ [i.e. $N_i(v)A_i$], which we discussed in Section 3.2.2.

We express adoption decision of i in the following latent variable (i.e. A_i^*) discrete choice model:

$$
A_i^* = \Theta_A\left(A_j, X_i, G_i, R_i\right) - \varepsilon_i \text{ with } A_i = \begin{cases} 1 & \text{if } A_i^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}
$$

where A_i is a binary indicator that equals 1 if household i adopts the improved soybean variety and zero otherwise. The other variables are as defined earlier, and R_i is an instrument excluded from equation (1), and used to identify the effect of household adoption decisions on the outcomes. Θ_A is a vector of

Table 2. Variable definition, measurement and descriptive statistics

Variables	Definition and measurement	Mean	SD
Panel A: *Household characteristics*			
Adoption	1 if farmer adopted the improved variety; 0 otherwise	0.67	0.47
Nadoption	Proportion of peers who adopted the improved variety	0.69	0.01
Sex	1 if male; 0 otherwise	0.59	0.49
Age	Age of farmer (years)	44.03	12.04
Education	Number of years in school	1.27	3.27
Hsize	Household size (number of persons)	5.64	2.14
HLand	Total land size of household (in hectares)	2.56	1.56
HWealth	Value of household durable assets in 10,000 GHS	1.29	2.00
HRisk	Risk of food insecurity (No. of months household was food inadequate)	0.93	1.37
Soil fertility	4 = fertile; 3 = moderately fertile; 2 = less fertile and 1 = infertile	2.97	0.97
Seed use	Quantity of soybean seeds used per acre in kilograms	9.58	4.37
Fertiliser cost	Cost of fertiliser applied per acre in GHS	151.40	226.10
Pesticide cost	Cost of pesticides applied per acre in GHS	1.45	5.26
Weedicide cost	Cost of weedicides applied per acre in GHS	22.52	37.18
Machinery	Log of machinery cost per acre	4.16	0.50
Local wage rate	Log of local wage rate per day	1.80	0.23
Labour use	Number of man-days per acre	14.95	10.21
Extension	1 if ever had extension contact; 0 otherwise	0.34	0.47
Farm revenue	Total farm revenue of household in 1000 GHS	6.37	4.23
Soybean income	Net income from soybean in GHS calculated as total soybean revenue per acre minus the cost of seeds, fertiliser, weedicide, labour and machinery used on soybean farm per acre.		
Association	Number of associations in which the farmer is a member in the community	1.07	1.27
Town centre	Distance from community to main town centre in kilometres	15.46	11.86
Panel B: *Instruments*			
SoySeed price	Soybean seed price in GHS/kilograms	1.06	0.19
SoySeed distance	Distance from household location to soybean seed source in kilometres	5.54	3.51
NResident distance	Average distance from farmer to peers' residence in kilometres	5.33	3.48
N²Resident distance	Average distance from peers to peers of peers' residence in kilometres	5.22	2.06
Panel C: *Direct peer characteristics*			
NSex	Proportion of male peers	0.65	0.17
NAge	Average age of peers	43.65	4.37

(continued)

Table 2. (Continued)

Variables	Definition and measurement	Mean	SD
NEducation	Average years of schooling of peers	1.58	1.12
NHsize	Average households' size (number of persons) of peers	5.74	0.79
NLandholding	Average landholdings of peers	2.67	0.67
NWealth	Average value of household durable assets of peers (normalised)	0.03	0.34
NSoil	Average soil fertility of peers	3.02	0.31
NExtension	Proportion of peers with extension contact ever	0.38	0.15
NFarm revenue	Log of average total farm revenue of peers	8.55	0.52
NSoySeed distance	Average distance from peers' household locations to soybean seed source in kilometres	5.52	3.30
Panel D: *Indirect peer characteristics*			
N^2Sex	Proportion of male peers of peers	0.63	0.13
N^2Age	Average age of peers of peers	43.73	3.82
N^2Education	Average years of schooling of peers of peers	1.51	0.92
N^2Hsize	Average households' size (number of persons) of peers of peers	5.73	0.74
N^2Landholding	Average landholdings of peers of peers	2.65	0.59
N^2Wealth	Average value of household durable assets of peers of peers	0.04	0.31
N^2Soil	Average soil fertility of peers of peers	3.01	0.29
N^2Extension	Proportion of peers of peers with extension contact ever	0.38	0.14
N^2Farm revenue	Log of average total farm revenue of peers of peers	8.56	0.51
N^2SoySeed distance	Average distance from peers' of peers household locations to soybean seed source in kilometres	5.51	3.28

parameters to be estimated. ε_i is an independent and identically distributed (i.i.d.) error term and because it enters the selection equation with a negative sign it represents the unobserved characteristics, also referred to as resistance, that make individuals less likely to adopt.

If we assume a cumulative distribution function (*c.d.f.*) of ε_i as $\Phi(\varepsilon_i)$, then the mean part of equation (2) [i.e. $\Theta_A(.)$] will represent the propensity score of adoption [defined as $\Phi(\Theta_A(.)) \equiv P(Z)$], which is based on the observed characteristics. The *c.d.f.* of ε_i represents the quantiles of distribution of the unobserved resistance to adoption [defined as $\Phi(\varepsilon_i) \equiv U_A$]. A farm household will adopt, if the propensity score of adoption is greater than the unobserved resistance to adoption [i.e. $\Phi(\Theta_A(.)) \geq \Phi(\varepsilon_i)$]. Given the propensity score and equation (1), we can estimate the outcome equation as a function of the observed regressors (A_j, X_i, D_i, G_i) and the propensity score $P(Z)$ as

$$E[Y|A_j = a, X_i = x, G_i = g, P(Z) = p] = A_j\rho_0 + X_i^{'}\eta_0 + G_i\tau + A_j^{'}(\rho_1 - \rho_0)p + X_i^{'}(\eta_1 - \eta_0)p + E(U_{1i} - U_{1i})p \quad (3)$$

where $Y = Y_{1i} - Y_{0i}$, $(\rho_1 - \rho_0)p$ and $(\eta_1 - \eta_0)p$ measure the returns to adoption for households with different levels of peer adopters, A_j, and other observable covariates, X_i, respectively. These observed gains could be positive or negative depending on whether households with higher values (such as more adopting peers) have higher or lower than average returns to adoption (Carneiro, Heckman and Vytlacil, 2011). $E(U_{1i} - U_{1i})p$ represents the returns to adoption due to unobserved ability of the household. Suppose that Y is yield, a positive (negative) effect of $E(U_{1i} - U_{1i})p$ will imply a negative (positive) selection on unobserved gains.

Following Heckman and Vytlacil (2005) and Cornelissen *et al*. (2018), we obtain the MTEs for A_j, X_i and $U_A = p$ by taking the derivative of equation (3) with respect to p as

$$\text{MTE}(a,x,p) = \frac{\partial E[Y|., P(Z) = p]}{\partial p} = A_j^{'}(\rho_1 - \rho_0) + X_i^{'}(\eta_1 - \eta_0) + \frac{\partial K(p)}{\partial p} \quad (4)$$

where $K(p)$ is a nonlinear function of the propensity score. Equation (4) suggests that treatment effect heterogeneity can result from both observed and unobserved characteristics. Estimation of the treatment effects requires a first stage in which the instrument, R_i, in equation (2) causes variation in the probability of adoption, conditional on the observed characteristics [i.e. $R_i \perp (U_{0i}, U_{1i}, \varepsilon_i) | (A_j, X_i, G_i)$]. Given the exclusion instrument, we estimate a first-stage probit equation (2) to obtain estimates of the propensity score $\hat{p} = \Phi(\Theta_A(.))$. Modelling $K(\hat{p})$ as a polynomial in degree 2, we estimate the MTE using the local instrumental variable (IV) estimator by expressing equation (3) as a function of observed regressors (A_j, X_i, G_i) and the propensity score $P(Z)$. This is specified as

$$Y = A_j\rho_0 + X_i^{'}\eta_0 + G_i\tau + A_j(\rho_1 - \rho_0)\hat{p} + X_i^{'}(\eta_1 - \eta_0)\hat{p} + K(\hat{p}) + \mu_i \quad (5)$$

where $K(\hat{p})$ is a non-linear function of the propensity score and μ_i is the error term. Equation (5) expresses the returns to adoption for an individual with adopting peers $A_j = a$, and observed characteristics $X_i = x$, who is in the U_Ath quantile of the distribution of ε. We compute the unconditional treatment effects of household adoption [i.e. the average treatment effects (ATEs), treatment effects on the treated (TTs) and treatment effects on the untreated (TUTs)] by aggregating MTE over U_A and the appropriate distributions of the covariates. Given our interest in evaluating policy intervention that seeks to subsidise soybean seed price or reduce distance to soybean seeds source, we also use the policy-relevant treatment effects (PRTEs) to estimate the aggregate effects of such policy changes (Heckman and Vytlacil, 2005) (refer to Appendix A1 for expression of these treatment effects measures).

4.2. Exclusion restriction and identification of the peer effect

The first identification concerns are issues of standard endogeneity and omitted variable biases of own adoption in equation (1), due to the fact that own adoption is endogenously determined. Our strategy for dealing with this is to rely on the distance of the household to the closest source of soybean seeds, and not necessarily where soybean seeds are actually purchased. We argue that distance to soybean seed source indicates the availability of the soybean seeds in the district and will likely alter the relative cost of adoption by a household (see also Suri, 2011). Thus, households located close to improved soybean seed source will have lower costs and possibly higher net benefits from adoption, which will make them more likely to adopt than those not closer. We further argue that distance to soybean seed source is not directly related to our outcome variables, except through the effect on adoption, because the main sources of the improved soybean variety are agricultural input dealers—some of who are located in the district capitals (CSIR-SARI, 2013).[13]

Two main possible concerns about the exogeneity of our instrument are that if soybean seed dealers chose their location strategically close to their buyers and if households' location was endogenously determined based on the location of input dealers. In respect of the first concern, we show that this is not the case with results of t-test of differences in means, across different distance bandwidths, for variables at the village level, household levels and the outcomes in Table A1 (Appendix A3). The tests suggest that villages and households located closer to soybean seed source are not systematically different from those located farther away. The second concern is not likely the case, because soybean is not the main crop cultivated by these households and, thus, it is unlikely that a household will change location because it wants to access improved soybean seeds. Table A1 further shows no significant difference in distance and adoption status among households who changed location over the past 5 and 10 years as at the time of the interviews.

The next critical issue of identification is the peer effects in equations (1) and (2). The first concern is the endogeneity of the peer effects. First, the peer adoption effect (i.e. A_j), in equation (1) cannot generally be consistently estimated, especially with Ordinary least squares (OLS), because of the correlation of the error term in this equation with this term [i.e. $\mathrm{cov}(A_j, U_{1,0i}) \neq 0$], possibly due to the omitted effects of the peer outcomes (Acemoglu, Garci-Jimeno and Robinson, 2015). The second aspect is that the estimation of own and peer adoption (A_j is endogenous effect) in equation (2) poses endogeneity concerns because of the Manski's (1993) 'reflection problem' and correlated unobservables [i.e. $\mathrm{cov}(A_j, \varepsilon_i) \neq 0$]. The reflection problem is the result

13 Of course, distance to seed source could be correlated with distance to town centre, where households who have their closest seed source located in the town centre inadvertently live closer to the town centre and are therefore more likely to be wealthy and to be able to buy or trade for food, increasing food security. This could threaten our identification strategy because distance to soybean source in this case can affect our outcomes through closeness to town centre and household wealth, and not only through adoption. For this reason, we controlled for distance to town centre and household wealth in all specifications.

of the coexistence of the endogenous peer effect and the contextual effect in equation (2).[14]

In order to identify the contextual effect in equation (1) and the contextual and endogenous effects in equation (2), we follow the approaches of Bramoullé, Djebbari and Fortin (2009) and Acemoglu, Garci-Jimeno and Robinson (2015), who use the average characteristics of peers of peers [i.e. $N^2(v)$] as an instrument for the average adoption of peers. Intuitively, since the characteristics of a household's peers of peers are correlated with the behaviour and outcome of the household's peers, but are exogenous to the behaviour and outcome of the household, these satisfy the exclusion restriction of being valid instruments for the adoption decision of the household's peers (see Appendix A2 for a case on social network structures and identification of peer effects). Two key requirements for the use of this strategy are that the peers of peers characteristics (such as distance to soybean seed source by peers of peers) used as instruments should be uncorrelated with the instrument used to identify own adoption and that the peers of peers instrument must be independent of own outcomes, except through average peer adoption (Acemoglu, Garci-Jimeno and Robinson, 2015).

However, given that our main instrument is the distance to soybean seed source, it is likely that the household's own distance to seed source will be correlated with the average distance to soybean seed source by peers of peers. As a result, we use the average distance between the residence of the household's peers and the peers of peers as an instrument to identify the effect of average peer adoption on household's own adoption and the outcomes. The reasoning is that, when farmers are residentially close to each other, they are more likely to interact and exchange information and resources, which can increase the likelihood of them influencing the behaviour and decisions of each other. Thus, if a farmer has geographically closed peers whose closer peers have new and more access to information about the improved variety, that farmer could receive this information and advice from the peers of peers through the farmer's peers.

Indeed, whereas the distance to soybean seed source of peers of peers appears to be highly correlated with own distance (0.942), the average distance between the residence of farmer's peers and the peers of peers is uncorrelated with own distance to the seed source (0.010) as shown in Table A2 (Appendix A3). To test the second assumption, we followed the approach of Di Falco, Veronesi and Yesuf (2011) by regressing the outcomes of non-adopters on the own and average peer adoption instruments in Table A3 (Appendix A3). Whereas the estimate generally show that these instruments do not significantly correlate with the outcomes, Tables B1.1 and C1–C3 in

14 These identification issues are discussed in the social networks and peer effects literature (Bramoullé, Djebbari and Fortin, 2009; Acemoglu, Garci-Jimeno and Robinson, 2015; De Giorgi, Frederiksen and Pistaferri, 2020). The formal development of these issues is beyond the scope of this paper. We refer the reader to Acemoglu, Garci-Jimeno and Robinson (2015) for the formal development and identification problems therein.

the supplementary material show that the instruments significantly explain average peer adoption and own adoption, respectively.

Thus, to account for the endogeneity of peer adoption, we regress peer adoption on own, X_i, and peer characteristics $(N_i(v)X_i)$, as well as the characteristics of the peer of peers $(N_i^2(v)X_i)$, obtain the predicted peer adoption, and use this as the peer adoption variable in the outcome equation (1) and selection equation (2) equations (see Table B1.1 in Appendix B1). Finally, we partly capture correlated effects by including village dummies to account for network fixed effects G_i (i.e. individuals self-select into networks based on network-specific characteristics). To account for correlated effects at the link formation level, we estimated a network formation model and inserted the predicted generalised residuals of this model into equations (1) and (2) as control functions (Brock and Durlauf, 2001) (see Appendix B2.).

5. Empirical results

5.1. First-stage adoption

Table 3 reports the marginal effects estimates of the first-stage probit selection model in column (1) for soybean yield and in column (2) for food and nutrient consumption. The distance to the closest soybean seed source is a strong predictor of adoption, and as expected, the coefficients of the distance suggest

Table 3. First-stage adoption results of yield and food and nutrient consumption specifications

	(1) Yield		(2) Food and nutrients	
	Coefficient	SE	Coefficient	SE
	Θ_A		Θ_A	
Nadoption (Predicted)	0.168***	0.047	0.110**	0.049
Sex	0.050	0.052	0.011	0.053
Age	−0.002	0.001	−0.002	0.001
Education	0.002	0.008	0.004	0.008
Hsize	−0.035**	0.013	−0.041***	0.013
HLand	0.052**	0.022	0.041*	0.021
HWealth (predicted)	0.163***	0.045	0.169***	0.045
Soil fertility	0.022	0.026	0.038	0.027
Seed use	−0.014**	0.006	−0.015**	0.006
Fertiliser cost	−1.8E-5	7.0E-5	−3.9E-5	6.0E-5
Pesticide cost	0.001	0.004	0.003	0.004
Weedicide cost	3.6E-4	0.001	−2.6E-5	0.001
Machinery	−0.006	0.052	−0.066	0.059
Labour use	0.001	0.002	0.001	0.002
Extension (predicted)	0.568***	0.110	0.572***	0.108
Soy selling price	0.166	0.203	0.088	0.194
Farm revenue (predicted)			0.270***	0.070

(continued)

Table 3. (Continued)

	(1) Yield		(2) Food and nutrients	
	Coefficient	SE	Coefficient	SE
	Θ_A		Θ_A	
Residuals_NWLink	−0.054	0.034	−0.046	0.034
Local wage rate	0.137	0.101	−0.266*	0.151
Network FEs	Yes		Yes	
Town centre	0.004*	0.002	0.005**	0.002
NSex	−0.240	0.151	−0.498***	0.163
NAge	0.003	0.005	0.002	0.005
NLand	−0.098**	0.040	−0.116**	0.040
SoySeed Distance	−0.478***	0.089	−0.483***	0.094
N^2SoySeed Distance	0.147***	0.027	0.144***	0.029
SoySeed price	−0.481**	0.193	−0.497**	0.194

Notes: The table reports the first-stage adoption results of the yield equation in column (1) and food and nutrient consumption equation in column (2). The estimates are marginal effects from probit selection model of adoption decisions (first-stage equation (2)). Our instrument is distance to soybean seed source, which is normalised about its overall mean. Θ_A is a vector of parameter estimates from equation (2). Network FEs is network fixed effects and Residuals_NWLink is residuals of the link formation model. SE are bootstrapped standard errors with 50 replications. ***, ** and * are significance at 1 per cent, 5 per cent and 10 per cent levels, respectively.

a strong relationship between the availability of the improved seeds and the decision to adopt. As expected, the soybean seed price shows a strong negative correlation with the decision to adopt. We also report the chi-squared test of the excluded instruments at the bottom panels of these tables, and based on this, we can, throughout, reject the hypotheses that the excluded instruments are not relevant.

The results suggest that there is a strong and significant relationship between the adoption decisions of peers and one's own decision to adopt the improved variety. To facilitate interpretation, we normalise peer adoption over its mean. Specifically, a standard deviation (SD) increase in the number of adopters of the improved variety among a household's peers raises the probability of the household's (own) adoption by at least about 11 per cent points. The estimated peer adoption effects correct for the potential endogeneity of the peer adoption variable by using predicted peer adoptions and account for correlated unobservables with the network fixed effects and residuals of the link formation model (Residuals_NWLink) in all specifications. The first-stage probit generates a large common support for the propensity score P(Z) and this ranges from 0.1 to at least 0.99 (Figure 1) for both soybean yield (part A) and food and nutrients (part B). This satisfies the requirement that the instrument should generate enough common support for the estimation of MTE (Cornelissen *et al.*, 2016).

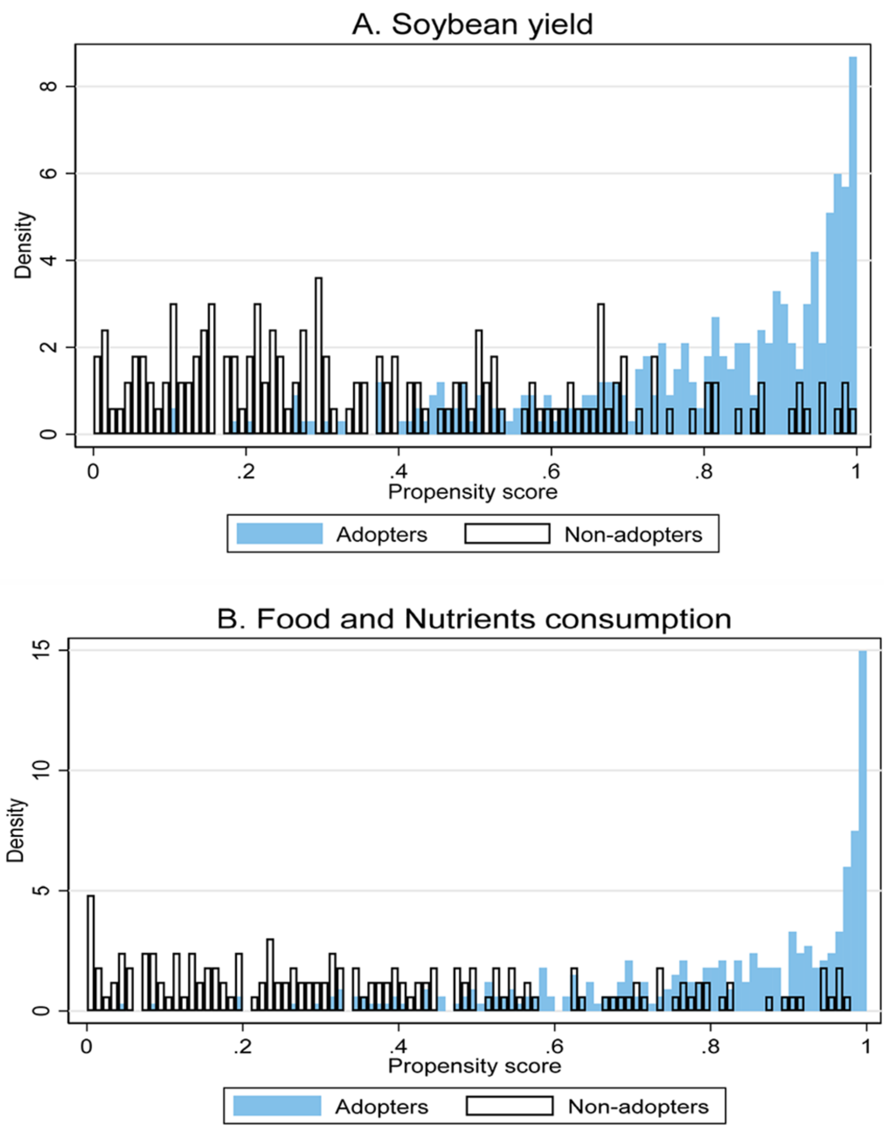

Fig. 1. Common support for soybean yield and food and nutrition security.
Notes: The figure plots the frequency distribution of the propensity score by adopters and non-adopters. The propensity score is predicted from the baseline first-stage regressions. Part A is based on the regression for soybean yield and part B is based on the regressions on food and nutrition. We have two different specifications of the first-stage equation and thus the two propensity score plots because we included extension contact in both the selection and the outcome stages in the yield equation, but included it only in the first stage of the food and nutrient consumption equations. The reason is that whereas extension was conceived as having potential effects on both adoption and yield directly, we considered that the effect of extension on food and nutrient consumption will be through farm income that we controlled.

Table 4. ATEs of adoption on yield and food and nutrient consumption

	(1) Yield	(2) Food	(3) Vitamin A	(4) Protein
Panel A				
ATE	0.606***	0.294***	0.526***	1.041***
	(0.095)	(0.080)	(0.121)	(0.198)
TT	0.772***	0.299**	0.596***	1.128***
	(0.149)	(0.118)	(0.173)	(0.284)
TUT	0.278**	0.283***	0.384***	0.864***
	(0.098)	(0.078)	(0.089)	(0.185)
Panel B				
Nadoption ρ_0	−0.051	0.087**	0.198***	0.292***
	(0.033)	(0.033)	(0.049)	(0.086)
TE for Nadoption $(\rho_1 - \rho_0)\widehat{p}$	0.128**	−0.107***	−0.214***	−0.346***
	(0.051)	(0.034)	(0.055)	(0.087)
p-values for essential heterogeneity	0.010	0.001	0.000	0.000
Observations	500	500	500	500

Notes: The table reports ATE, TT, TUT, effect of peer adoption (i.e. Nadoption ρ_0) and treatment effect of peer adoption [i.e. TE for Nadoption $(\rho_1 - \rho_0)\hat{p}$] using the baseline specification and the ρ's are as defined in equations (1) and (3). The yield column (1) refers to the soybean yield equation. The food, vitamin A and protein columns (2–4) refer to the food consumption, and vitamin-A- and protein-rich food consumption equation (estimates of other variables are in Tables C1–C3). The p-value for the test of essential heterogeneity tests for a non-zero slope of the MTE curve. Bootstrapped standard errors with 50 replications are reported in parentheses. *** and ** are significance at 1 per cent and 5 per cent levels, respectively.

5.2. Summary treatment effects and marginal treatment effects of household adoption

We report the summary treatment effect estimates of equation (5) in panel A of Table 4 (refer to Tables C1–C3 in Appendix C for the complete estimates). ATE indicates that for a soybean-producing household chosen at random from the population of soybean-producing households, adopting the improved variety increases soybean yield by 61 per cent points. Our results for TT imply that for an average adopting household, adoption significantly results in about 77 per cent points increase in soybean yield. In the TUT case, for an average non-adopting household, adoption would significantly increase soybean yield of the household by 28 per cent points.

Similarly, for a soybean-producing household picked at random from the soybean-producing population, adoption of the improved variety increases food and nutrient consumption from 29 per cent points for food to about 104 per cent points for protein. These estimated parameters are all statistically significant at the 1 per cent level. Also, the TT estimates show that for an average adopting household, adoption results in 30 per cent points increase in food consumption and 60–113 per cent points increase in nutrient consumption. These parameters are significantly different from zero, at least, at the 5 per cent level. The significance of adoption is still observed even in the untreated

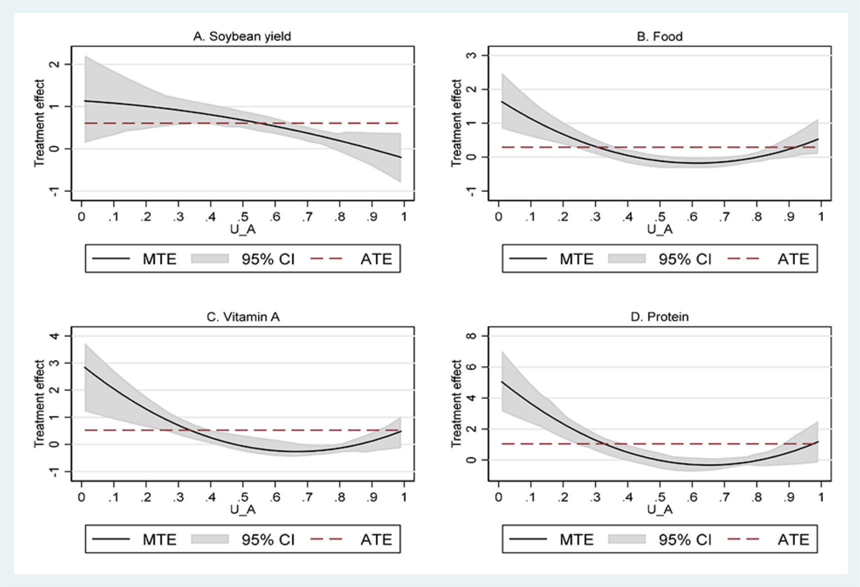

Fig. 2. MTE curves for soybean yield.
Notes: The figure shows the MTE curves for yield and food and nutrient-rich food consumption at the average values of the covariates based on specifications in equations (4) and (5). U_A denotes unobserved resistance to treatment/adoption. Part A is the MTE curve for soybean yield. Part B depicts the MTE curve for food consumption, part C shows the MTE curve for vitamin-A-rich foods consumption and part D is the MTE curve for protein-rich foods consumption. The dashed lines are ATEs. The 95 per cent confidence interval (95 per cent CI) is based on bootstrapped standard errors with 50 replications.

case, where the food and nutrient consumption of non-adopters will increase by 28–86 per cent points if they adopt the improved variety.

The summary measures of treatment effects suggest possible treatment effect heterogeneity among soybean-producing households. In particular, all parameter estimates in Table 4 show that TT is greater than ATE, which is also greater than TUT. This is suggestive of positive selection on gains, where individuals who are more likely to adopt (perhaps because of their innate ability or variation in the quality of adoption and production conditions) tend to benefit more from adoption in terms of yield and food/nutrient consumption. However, as indicated earlier, these summary measures mask such treatment effect heterogeneity, and thus, we show MTEs in Figure 2. These figures relate the unobserved parts of the outcomes ($U_1 - U_0$) to that of the adoption decision (U_A). Higher values of U_A imply lower probabilities of adoption (i.e. higher resistance to adoption).

The MTE curves decline with increasing resistance to treatment in all instances and indicate a pattern of positive selection on gains. In effect, given the unobserved characteristics, households who are most likely to adopt the improved variety appear to benefit the most from adoption. Thus, the slopes of the MTE curves in each case suggest a pattern of heterogeneity in returns to adoption, which is significantly different from zero at the 5 per cent level (see the *p*-values for the test of essential heterogeneity at the bottom of Table 4). Part A of Figure 2 depicts the MTE for yield and shows that for households who are more likely to adopt than the average household ($U_A < 0.5$), their returns to adoption are higher than the average household *albeit* not significantly different from the returns to adoption of an average household. For the households with higher resistance to adoption than the average household, their yield returns to adoption is significantly lower than that of the average household selected at random for the 30 per cent of households with the highest resistance to adoption ($U_A > 0.7$).

Figure 2 also shows that there is clear heterogeneity in returns to adoption in terms of food and nutrient consumption. We observe a similar pattern of positive selection on gains, with returns to adoption significantly higher for the 20 per cent and 25 per cent of households who are most likely to adopt than the average household for food and nutrients consumption, respectively. Figure 2 further shows that returns to adoption in terms of food and nutrient consumption decrease and fall below that of the average soybean-producing household, for the households with over 33 per cent (i.e. $U_A > 0.33$) resistance to adoption.

In order to probe for the source of this treatment effect heterogeneities, we check whether the positive gains on selection of unobserved characteristics (i.e. $U_1 - U_0 \,|\, U_A = u_A$) are because of heterogeneity in the outcomes when not adopting [i.e. upward sloping in $E(Y_0 \,|\, U_A = u_A)$], when adopting [i.e. downward sloping $E(Y_1 \,|\, U_A = u_A)$] or both. We report the plot of Y_1 and Y_0 for the various outcomes in Figure C1. The figure shows, across all outcomes, that the differences in the outcomes are driven by worse outcomes in the non-adoption state, as shown by the increasing dashed dotted lines. However, the outcomes in the adoption state (i.e. dotted lines) are more homogenous throughout.

5.3. Treatment effect heterogeneity in peer adoption

For easy reference, we report the estimates of peer adoption effects in panel B of Table 4, where we first present the effect for the case when the household is not adopting (i.e. ρ_0) and when the household is adopting [i.e. $(\rho_1 - \rho_0)\hat{p}$]. The results show that in the non-adoption state, an SD increase in the number of adopting peers of the improved soybean variety is associated with a decrease in one's own soybean yield, although not statistically significant. However, the treatment effect of peer adoption is significantly positive and increases own yield by about 13 per cent points.

In respect of food and nutrient consumption, the results show that when not adopting, an SD increase in peer adoption increases food consumption of the household by 9 per cent points and consumption of vitamin-A- and protein-rich foods by 20 and 29 per cent points, respectively. These effects are significant at least at the 5 per cent level and suggest that non-adopting households benefit from their adopting peers in terms of enhanced food and nutrient consumption. Interestingly, when the household adopts, the treatment effect of an SD increase in adopting peers is negative [i.e. $(\rho_1 - \rho_0)\hat{p}$], suggesting that household adoption of the improved variety significantly reduces the heterogeneity in food and nutrient consumption due to adopting peers by 11, 21 and 35 per cent points for food, vitamin A and protein consumption, respectively. These results indicate that households with more (fewer) adopting peers tend to gain more in terms of increased soybean yields (food and nutrient consumption), when they adopt than their counterparts with fewer (more) adopting peers. This is not surprising because as shown in Table 1 non-adopters appear to have lower yields and food consumption.

5.4. Effect mechanisms

Given the generally positive effects of adoption of the improved variety on yields and food and nutrient consumption, we next investigate the mechanisms by which adoption can affect food and nutrient consumption in particular. Our conceptual framework suggests that own adoption can enhance consumption through increased yields and changes in household income, consumption of own production, food prices and intra-household dynamics.[15] This analysis is shown explicitly in Table 5, where we first estimate the levels and heterogeneity effects of gains in yield from adoption on soybean income and food and nutrient consumption (columns 1–4). The estimates reveal a significantly positive association between gains in yield and income from soybean. In particular, a log per cent point increase in yield from adoption of the improved variety significantly increases the gains in soybean income by over GHS 700 [i.e. $(\eta_1 - \eta_0)p$], which is about 30 per cent higher than the mean soybean income of non-adopters.

In addition, food and nutrient consumption gains from increased yield due to adoption are positive, but significant for food and vitamin A and not significant for protein. This is expected, given that soybean is not a staple food consumed by households, but a crop that is primarily produced for sale to enhance household income. Following this, we next check the effects on food and nutrient consumption, given the income gains from adoption (columns 5–7). In effect, whereas at the non-adoption state increase in household income is significantly and positively associated with increased food and nutrient consumption, the nutrient consumption, in particular, is significantly higher for non-adopters when they adopt, as revealed by the negative treatment effects for income.

We also noted in the conceptual framework that the effect of agricultural production on food and nutrient consumption can be mediated by gender-related issues (Carletto *et al.*, 2015). Interestingly, Table 5 shows that the

15 Given the macro nature of food prices and the focus of the analysis on farm-level links, and the limitation of data on the sources of households' food and nutrient consumption (i.e. whether from own production or purchases), we are unable to show the effects of changes in food prices and consumption of own produce on food and nutrient consumption.

Table 5. Estimates of effects mechanisms

Soybean	(1) Soybean income	(2) Food	(3) Vitamin A	(4) Protein	(5) Food	(6) Vitamin A	(7) Protein
Yield η_0	653.4***	0.084	0.027	0.112			
	(34.1)	(0.208)	(0.335)	(0.545)			
TE for yield $(\eta_1 - \eta_0)\widehat{p}$	764.5***	0.467*	0.833**	1.057			
	(50.6)	(0.247)	(0.414)	(0.740)			
Income η_0					0.211***	0.476***	0.545***
					(0.069)	(0.143)	(0.163)
TE for income $(\eta_1 - \eta_0)\widehat{p}$					−0.030	−0.395**	−0.497**
					(0.079)	(0.165)	(0.196)
Sex η_0					0.103*	0.148	0.140
					(0.055)	(0.102)	(0.117)
TE for sex $(\eta_1 - \eta_0)\widehat{p}$					−0.905	−0.130	−0.126
					(0.069)	(0.126)	(0.158)
Observations	500	500	500	500	500	500	500

Notes: The table shows the effect pathways of adoption of the improved soybean variety. η_0 presents effects of yield and income on soybean income and food and nutrient consumption when the household is not adopting as in equation (3). $(\eta_1 - \eta_0)\,\hat{p}$ shows the treatment effects on consumption due to yield and income gains from adoption also as in equation (3). TE denotes treatment effect.

Table 6. Policy simulations of the effects of changes in soybean price and distance to soybean seed source on soybean yield and food and nutrient consumption

		Soybean seed price		Distance seed source	
	(1)	(2)	(3)	(4)	(5)
	Baseline propensity score	Policy propensity score	PRTE	Policy propensity score	PRTE
Soybean yield	0.664	0.819	0.421***	0.829	0.361***
			(0.082)		(0.109)
Food	0.665	0.823	0.205***	0.828	0.275***
			(0.055)		(0.055)
Vitamin A	0.665	0.823	0.323***	0.828	0.373***
			(0.078)		(0.072)
Protein	0.665	0.823	0.733***	0.828	0.859***
			(0.099)		(0.109)

Notes: The table presents PRTEs per net household shift into adoption for two different policies. Column 1 reports the baseline propensity score and columns 2 and 4 report the increase in the propensity induced by the soybean price subsidy and increased proximity to seed source, respectively, based on the baseline specification for the various outcomes. Columns 3 and 5 are PRTEs for the soybean seed and seed proximity policies, respectively. Bootstrapped standard errors (50 replications) are reported in parentheses. *** indicates significance at 1 per cent level.

treatment effect of adoption is not statistically significant across gender for all the outcomes, although the negative sign suggests females tend to benefit more from adoption in terms of food and nutrient consumption compared to males. This finding confirms that the main mechanism by which adoption affects food and nutrient consumption is through increased soybean yields and household income. It further suggests that the attenuating treatment effects of peers observed when a farmer adopts can be attributed to increased household income following own adoption.

5.5. Policy strategies

Our results so far have demonstrated that adoption of the improved variety does not only lead to increased soybean yield but also contributes to increasing food and nutrient consumption of not only adopters but that of non-adopters should they adopt. This implies that policies that seek to overcome structural barriers and induce people to adopt can be much rewarding. Thus, we show the effects of a policy that reduces soybean seed price by 50 per cent (in line with current government policy in Ghana) and a policy that reduces the distance of the household to the nearest soybean seed source to a maximum of 4 km, using PRTEs. Whereas the subsidy policy seeks to improve affordability, the distance policy attempts to enhance availability of the seeds of the improved variety.

Column 1 of Table 6 shows the propensity score at the baseline policy; columns (2) and (3) show the propensity scores and PRTEs, respectively, for soybean seed price subsidy; and columns (4) and (5) show the propensity scores and PRTEs, respectively, for the policy of reducing distance to soybean seed source. The estimates show that subsidising soybean seed price by 50 per cent and reducing the distance to soybean seed source to a maximum of 4 km shift households with high unobserved resistance to adoption into adoption and as a result significantly increase soybean yield by 42 and 36 per cent points, respectively, per household shifted from non-adoption into adoption. The magnitude of the price subsidy effect on yield is higher than that of the distance to seed source. We find statistically significant policy effects for both policies in food and nutrient consumption, but with marginally higher effects for the reduction in distance to seed source. These findings show that, whereas reducing distance to soybean seed source appears to be more effective in promoting food and nutrient consumption through adoption than the price subsidy, the subsidy appears to produce higher yield effect than the policy of reducing the distance to soybean seed source.

5.6. Robustness

In order to examine the robustness of our estimates, we examine the sensitivity of our results to changes in alternative specifications of the MTE functional form, outcome and selection equations, as well as in the peer effects. We first consider the baseline pattern of our MTE curve of positive selection on gains. This is because the estimation of the MTE depends on the functional form assumptions invoked, and also the MTE obtained under different functional form assumptions may yield different weighted effects of the instrument (i.e. IV effects) (Heckman and Vytlacil, 2005). In Figure C2 in Appendix C, we present MTE curves that include specifications based on the parametric normal model (which assumes returns to adoption decrease monotonically with resistance to adoption), parametric cubic and a semiparametric approach. These curves suggest that the basic shape of the MTE curve is robust to different functional forms and generally show a similar pattern as in the baseline specification.

We next consider the sensitivity of our ATE, TT and TUT to different specifications, as these put most weights in different segments of the MTE and therefore could be sensitive to changes in the estimated MTE (Carneiro, Heckman and Vytlacil, 2011). In panel A of Table C5, we present estimates from a model where we control for other contextual peer effects (i.e. peers' sex, age, landholding and soil fertility) in the outcome equations (columns 1–3) to assess whether the observed peer and treatment effects could be driven by contextual effects or correlation in soil conditions between farmers and their peers. In columns 4–6, we present estimates of a specification that excludes the effects of peer adoption to examine these estimates under the stable unit treatment value assumption (SUTVA).[16] The estimates are marginally low and

16 The SUTVA requires that the potential outcomes of treatment observed on one farm household should not be affected by the treatment of other farm households. The inclusion of the peer adoption effects violates this assumption but Manski (2013) provides characterisation of bounds

high for yield and food consumption (columns 4–6) and suggest expansion and attenuation biases, respectively, *albeit* similar in directions and significance to the baseline estimates.

In columns 1–3 of panel B, we report estimates when estimating the first stage with a squared term of distance to nearest soybean seed source as additional instrument to account for the fact that at longer distances to seed sources the probability of adoption will become very low. In columns 4–6 of panel B, we interact distance to soybean seed source with household wealth and household size because the effect of our instrument is likely to vary across households, based on their observed resource status (Carneiro, Heckman and Vytlacil, 2011). Table C6 reports results that show the sensitivity of the estimates to the use of standard errors clustered at the village level in columns (1)–(3) (Cameron, Gelbach and Miller, 2008) and when we control for mobile phone network coverage in the village in columns (4) and (5). In order to show the sensitivity of the results to changes in the measure of household food consumption, we report treatment effects of adoption on household dietary diversity in column (6) of Table C6 (FAO, 2010). In spite of these exercises, the treatment effects estimates remain qualitatively similar to those reported in Table 4.

Finally, Table C7, columns (1)–(3) of panel A, explores the sensitivity of the estimates to peer effects through means other than peer adoption. Recall from Section 3.2.2 that links in our networks are defined using social and farm plot proxies, and some of these (such as labour and land exchanges) can present effects similar to peer adoption effects. We explore this by accounting for household (node) degree, which is the total number of connections a household has in the network. A related concern is the issue of the use of the sampled networks that truncate the number of households' social connections and could lead to important links and nodes not observed, which can bias the estimates (Chandrasekhar and Lewis, 2016). In order to examine the sensitivity of our estimates to this issue, we follow the approach of Liu, Patacchini and Rainone (2017) by re-running our models without households with links with all the five randomly matched households to them. Finally, in columns (1)–(3) of panel B, we report estimates with difference in adopting peers of a household between a year after the introduction of the improved variety (i.e. 2004) and the 2016 cropping season. The results of these exercises remain very similar to our baseline results in Table 4, suggesting that our findings of the pattern of selection and the treatment effects are robust to various functional forms and specifications.

6. Discussion

We find significant effects of household adoption on yield and food and nutrient consumption as expected, which can be partly attributed to the yield,

on the treatment effects under social interactions, and thus our estimates should be interpreted as bounds and not necessarily as the point estimates.

income and agro-climatic advantages of the improved over the traditional variety (CSIR-SARI, 2013). The high magnitudes of these effects, especially on food and nutrient consumption, can be explained by the interplay of two factors: one is the timing of the survey, as it was conducted in the lean season when households rely heavily on food consumption from cash purchases, and the commercial status of soybean, as an income-enhancing crop for households (see also WFP and GSS, 2012; Carletto *et al.*, 2015).

Our findings of heterogeneity in returns to adoption show that households with low resistance to adoption do much worse than an average soybean-producing household without adoption of the improved variety. However, these households become relatively similar with adoption. This is perhaps because the production of the traditional variety is more demanding (in terms of time and labour) and requires farmers to invest more resources to minimise the production challenges. This could increase the risk of vulnerable households who are not able to meet these production requirements of losing their crops or entire investment due to early shattering. But the improved variety is quite resistant to these issues (CSIR-SARI, 2013).

Whereas peer adoption effect has significant and positive effect on households' yields when adopting, we find no significant peer effect on yield when the household is not adopting. A potential interpretation is that when the household is not adopting, increased peer adoption could reduce private learning opportunities from peers, especially if the production processes of the improved and traditional varieties are not complementary. However, household adoption increases private learning and imitation opportunities from adopting peers (Niehaus, 2011).

Our findings on peer adoption effect on food and nutrient consumption in the non-adoption state are suggestive of some form of private transfer among peers, since consumption increases with peer adoption in the non-adoption state. However, own adoption leads to attenuating peer adoption effects, and this can primarily be attributed to the yield and income gains from the improved soybean variety that tend to substantially increase the consumption of non-adopters when they adopt. This indicates that consumption benefits from peer adoption tend to decline with own adoption, suggesting that increased own productivity and household income lead to reduction in farmers' dependence on peers (Alger and Weibull, 2012; Di Falco *et al.*, 2018).

7. Conclusion

This paper examined the impact of adoption of improved soybean variety on soybean yield and household food and nutrient consumption, using household survey data from Ghana. In particular, we estimated MTEs of adoption of the improved variety on these outcomes and, thus, show heterogeneities in returns to adoption due to observed and unobserved characteristics of households. The results generally show a positive association between adoption and the outcomes, but do not necessarily establish causality. We note three main findings: First, a pattern of positive selection on unobserved gains from adoption of the improved variety is observed across all outcomes, which is due to the fact that households who are more likely to adopt the improved variety have lower returns than that of an average soybean-producing household, when not adopting. This finding is in line with the hypothesis of adoption based on comparative advantage (Suri, 2011). However, adoption of the improved variety tends to make these households quite homogeneous across these outcomes, suggesting that adoption can serve as means by which poorer households can narrow the gaps in yields and food and nutrient consumption with better and richer households.

Second, we find that households benefit, in terms of increased soybean yield, from having peers who are adopters only when the households also adopt, suggesting the possibility of social learning, imitation and/or exchange of resources that are complementary in the soybean cultivation process. However, on food and nutrient consumption, we find that having adopting peers results in increased household food and nutrient consumption, when the household is not adopting but attenuates when the household adopts. This suggests that households tend to depend on peers more in meeting food and nutrient consumption when not adopting (possibly in the form of private transfers), which decreases when the household adopts. These findings suggest that network effects can be an important means of promoting adoption of the improved variety and food and nutrient consumption of vulnerable households. Interventions, such as self-help groups and/or farmer field-days, aimed at promoting interactions among farm households and enhancing exchange can increase the effectiveness of social networks in promoting adoption, soybean yield and household food security and nutrition.

Finally, subsidising soybean seed price and reducing distance to soybean seed source are estimated to increase adoption, soybean yield and household food and nutrient consumption. This implies that interventions to minimise production and structural constraints to adoption could be an important strategy in mitigating the cost associated with technology adoption, at least in the setting at hand. Whereas our evidence suggests that input subsidy is likely to be a move in the right direction in enhancing adoption and household outcomes, the option of increasing access by reducing the distance to soybean seed source could produce some additional gains in food and nutrient consumption. Hence, government and development partners can consider increasing access through availability of the improved seeds at the local levels, such as empowering village-level shops or community-based groups to engage in input marketing.

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Supplementary data

Supplementary appendix and data are available at *ERAE* online.

Conflict of interest

The authors declare that they have no conflict of interest.

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