Can Crop Commercialization Help Promote Land Productivity? Evidence from Cambodia's Paddy, Maize, and Cassava Farming

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ABSTRACT

This paper investigates the degree to which crop commercialization can help promote land productivity in agricultural production systems in Cambodia. Drawing on the most recent wave of the Cambodian Inter-Censal Agriculture Survey in 2019 as well as historical data from the Cambodia Agriculture Census in 2013, we examine trends in land productivity and crop commercialization for the four most-produced crops in Cambodia including non-aromatic paddy, aromatic paddy, maize, and cassava. Land productivity is measured by yield per hectare per harvest, and crop commercialization by the intensity of market participation. An instrumental variable (IV) approach is applied to correct for possible endogeneity of crop yields and crop commercialization. Findings suggest that crop commercialization is significantly associated with increased land productivity. Farmers with greater intensity of crop sales are more likely to use fertilizers, pesticides, and irrigation. They are also more likely to obtain agricultural training and acquire agricultural loans. These results provide support for recent calls to policymakers in Cambodia to focus on enhancing market opportunities for producers, helping farmers move from subsistence to more market-oriented farming as a pathway to increased productivity and incomes, alongside direct efforts to make fertilizers, pesticides, irrigation, agriculture training and loans more accessible to farmers.

Keywords: Crop commercialization, yield, land productivity, instrumental variable (IV) regression, agriculture, Cambodia

I. INTRODUCTION

The emergence of the COVID-19 pandemic has crippled the global economy and undermined the significant progress toward global poverty reduction in the last quarter century. According to the World Bank's 2022 report, the rise in extreme poverty in 2020 is estimated to be the most severe since the start of consistent global poverty tracking in 1990. The global extreme poverty rate increased from 8.4 percent in 2019 to an estimated 9.3 percent in 2020. This means that more than 70 million additional people were living in extreme poverty by the end of 2020, raising the global total to over 700 million. Since then, economic recovery has been uneven with a much faster pace of recovery in the richest economies than in low- and middle-income economies. These setbacks and slow recovery have pushed the world further away from achieving the UN's targets for Sustainable Development Goal 2: Zero Hunger (SDG2) by 2030. The current projection is that about 8% of the world population, equivalent to nearly 670 million people, will continue to face hunger in 2030 (FAO, 2022).

Increasing incomes in the food and agriculture sector is crucial to achieving SDG2 globally, and even more so in the case of Cambodia where agriculture occupies a large share of GDP, employment, and trade (ADB, 2021). In Cambodia, crop cultivation is characterized by mostly low-input, low productivity, small-scale farming with an average landholding size of only 1.3 ha (ADB, 2021). Many of the poorest and most vulnerable depend primarily on the agricultural sector for their livelihoods (Eliste and Zorya, 2015). Raising productivity and incomes of these smallholder farmers is thus one of the key targets in SDG2. Previous studies have shown how Cambodia's low level of farm productivity is associated with constraints on input use such as irrigation, fertilizers, and pesticides, compounded by limited access to improved technology and productive assets (see, for example, Chhim et al.; 2020; Chun, 2014; Kea et al., 2016; Yu and Fan, 2011). This paper asks, beyond the generally positive potential impacts of expanded input use suggested by previous studies (McArthur and McCord, 2017), to what degree does crop commercialization play a role in promoting land productivity in Cambodian agricultural systems?

This question is particularly important for Cambodia's farm productivity growth, and hence poverty reduction for at least three reasons. First, despite an impressive average economic growth rate of 7.6% over the last two decades (ADB, 2021), Cambodia's ability to improve land productivity through expanding access to agricultural inputs remains limited, although input use has been on the rise (ADB, 2021). Second, as general trade theory suggests, trade has the potential to make farmers better off by allowing them to specialize in growing crops in which they have a comparative advantage. Specialization enables farmers to acquire highly specific production skills and adopt improved agricultural techniques, thus leading to increased productivity (Govereh and Jayne, 2003). Finally, Cambodia's agriculture policies have aimed at promoting crop production and exports (Eliste and Zorya, 2015). The rising trend of crop exports in recent years, and by extension commercialization, possibly offers another link between commercialization and productivity growth. Increasing productivity through policy efforts seeking to enhance market access such as infrastructure investment may support both increased commercialization and increased crop production. However, if such potential positive impacts are not borne out by the data, it may be that national agriculture policies should focus on other avenues besides efforts to promote commercialization in order to enhance productivity.

This study seeks to contribute to these active policy debates by examining the role of crop commercialization in improving land productivity among rice, maize, and cassava farmers in

Cambodia. Rice, maize, and cassava are the core of Cambodia's crop sector with the combined gross production value of about 88% of all crops' value in 2019 (Food and Agriculture Organization Corporate Statistical Database, 2021). Drawing on data from the Cambodia Inter-Censal Agriculture Survey in 2019 (CIAS19) and the Cambodia Agriculture Census in 2013 (CAC13), we use an instrumental variable (IV) analysis approach to identify possible effects of expanding crop commercialization on increased crop productivity. In line with previous studies in the literature (see Strasberg et al, 1999; von Braun et al., 1995), we use a detailed measure of commercialization – the Household Crop Commercialization Index (HCCI) – as an indicator of the intensity of crop commercialization by households, with crop yield (the amount of crop per harvest per hectare of cultivated land) as the dependent variable. We further analyze the channels through which the effects of commercialization on crop yields might be realized, and also consider potential differences across large-scale and smaller-scale farm sizes[1] and across crop types.

This study contributes to the existing literature on agriculture commercialization and productivity in at least three key ways. First, using a relatively large sample of newly released CIAS19 data, it adds to the nascent literature that examines agricultural productivity at the farm-household level in Cambodia. More specifically, it represents the first study to empirically investigate the effect of crop commercialization on productivity across crops in the Cambodian context. Second, many existing studies have struggled to establish causality between crop commercialization and crop productivity due to the high potential for endogeneity and the lack of appropriate instrumental variables. To fill this void, we are able to exploit village level infrastructure variables from a 2013 agricultural census dataset as a source of instruments. This enables us to employ a two-stage least-squares (2SLS) estimation method representing a substantial methodological advance over previous empirical studies of crop commercialization and agricultural performance. Third, in contrast to many studies in the literature which rely on annual production estimates, we are able to calculate land productivity as the crop yield per hectare per harvest, accounting for the possibility of multiple crop harvests on a given parcel per year. We are also able to measure crop commercialization on a continuous scale, rather than as a simple binary variable as used in many past studies. Finally, the paper further investigates how the impacts of commercialization on productivity vary across farm size and crop type, while also examining multiple potential impact channels through which commercialization might impact productivity (namely via increased use of key agricultural inputs including fertilizer, pesticides, irrigation, and farm credit).

The remainder of the paper is organized as follows: In Section II, we present the conceptual framework which is followed by the description of the data on household land productivity and crop commercialization by province in Section III. Section IV summarizes the empirical methods, and in Section V the estimation results are presented. Finally, Section VI concludes and discusses potential policy implications.

II. CONCEPTUAL FRAMEWORK

Market participation of smallholder farmers has been documented in several previous studies as an effective way to boost agricultural productivity. An early study by Strasberg et al. (1999) using

[1] Foster and Rosenzweig (2022) show that there is a U-shaped relationship between farm size and productivity. That is, the smallest and largest farms are most efficient in their use of labor; thus, they are often more productive than medium-sized farms. That is in part because labor is substantially underutilized in intermediate production scales relative to in smaller and larger farms. Therefore, in this study we further extend our focus into the potential links between farm size and relationships between crop commercialization and farm productivity.

data from Kenya found a positive association between food crop productivity and cultivating market-oriented cash crops such as cotton and groundnuts. The authors noted that by taking advantage of the delivery and credit channels established through government programs targeting cash crops, farmers were able to increase adoption of fertilizer and invest in more labor and productive assets for food crop farming. Using data from Gokwe North District in Zimbabwe, Govereh and Jayne (2003) similarly found that households engaging in a cotton commercialization scheme had higher food crop yields than non-cotton and marginal cotton producers. The authors also highlighted that the presence of commercialization schemes in a particular area was associated with infrastructure investments that benefited all farmers in the region.

On the other hand, not all past studies show a positive association between crop commercialization and crop productivity. For example, Rios et al. (2009) analyzed the relationship between farm productivity and market participation based on data from Tanzania, Vietnam and Guatemala, and found no consistent evidence of an impact of market participation on productivity. The authors conclude that increasing commercialization may be productivity-enhancing over time, but that an association might not be evident in a cross-sectional study.

We are aware of no previous studies that empirically test the association between crop commercialization and food crop productivity across crop types at the farm-household level in Cambodia. In the following section we describe the conceptual framework guiding variable selection, measurement, and analysis in the present study.

2.1 Defining productivity and commercialization

Drawing on previous literature we measure productivity as land productivity, and commercialization as the intensity of participation in market sale of crops produced. One common measure of land productivity is total annual gross output per unit of land (see, for example, Govereh and Jayne, 2003; Strasberg et al., 1999). This is fine if all plots are cultivated only once or there is the same number of harvests for all the farms. However, in Cambodia there is a varying number of harvests across farms depending on location and access to irrigation systems. We also measure productivity at the household level, but the CIAS 2019 data consist of households who possess multiple plots. Therefore, to obtain a consistent measure, we choose to measure household-level land productivity as the average yield per hectare of cultivated land per harvest.

$$Yield_{hj} = \frac{\sum_i q_{hji}}{\sum_i a_{hji} m_{hji}} \tag{1}$$

where $Yield_{hj}$ is the quantity of crop *j* per hectare per harvest for household h. q_{hji} is the quantity of crop *j* harvested from plot i, m_{hji} is the number of harvests, and a_{hji} is the cultivated area measured in hectares.

We measure crop commercialization by the intensity of participation in market sales or the Household Crop Commercialization Index (HCCI) (see Strasberg et al., 1999; von Braun et al., 1995).[2] Some previous studies measure commercialization as a binary indicator variable for *any* market sales (see Khun and Lim, 2022). However, a continuous variable is a more appropriate

[2] While commercialization can occur in either input or output markets, we focus on the latter. In fact, commercialization on input and output sides tends to occurs concurrently (Pingali,1997).

measure since small or subsistence farms in Cambodia often divide their harvests into some combination of consumption and sales. We calculate HCCI as:

$$HCCI_{hj} = \frac{\sum_i s_{hji}}{\sum_i q_{hji}} \times 100 \qquad (2)$$

where s_{hji} is the sale quantity of crop j.

An HCCI value of zero characterizes households with zero market sales (i.e., subsistence production) and as the value approaches 100, a greater percentage of crop production is marketed, indicating increasing intensity of commercialization. One important advantage of the HCCI is its relativity to production volume. For instance, in cases where a small farm sells most of the output and a large farm sells a small share of theirs, even with the same absolute amount of crop sold, HCCI for the former will be greater than the latter.

2.2 Commercialization-productivity nexus

There is a large literature supporting a hypothesized relationship between agricultural commercialization and farm productivity, with the transition from subsistence to commercial agriculture regularly cited as one of the driving forces of economic growth and poverty reduction in low-income countries (de Janvry and Sadoulet, 2009; Hazell, et al., 2010; Govereh and Jayne, 2003; Townsend, 2015). By exploiting comparative advantage, the progressive move toward a market-oriented system of agricultural production is expected to encourage household specialization while promoting national diversification (Dorsey, 1999; Huang et al., 2004; Kim et al., 2012; Pingali, 1997; Timmer, 1997; Udoh et al., 2011; von Braun, 1995). Specialization can increase productivity as farmers acquire specific production skills and adopt more modern agricultural techniques (Govereh and Jayne, 2003). Traditional farming methods such as the use of animal traction may also be replaced by more productive hired or purchased mechanized equipment for ploughing, planting, weeding, or harvesting.

Besides specialization, commercialization could serve to promote efficiency and greater output through improved access to inputs. As farms become increasingly commercialized, they are likely to reduce reliance on own-produced inputs such as manure and saved seed while sourcing more inputs such as improved seed, inorganic fertilizer, and pesticides from the market (Leavy and Poulton, 2006). Additional hired labor may also be required to cope with expanding cultivated area, particularly where commercialization is associated with farm consolidation. To the extent that this increased market integration is associated with farm productivity gains, the resulting improvement in household incomes has the potential to induce further asset accumulation (Paul et al., 2022), including additional investment in productive technologies further enhancing productivity.

However, there is clearly also a potential for reverse causality between productivity gains and crop commercialization. Improved farm productivity directly leads to increasing production and increased income, which may in turn lead to a greater intensity of crop commercialization (Abu et al., 2016; Rios et al., 2009; Wickramasinghe and Weinberger, 2013; Emran and Shilpi, 2012). Weinberger (2013) states that productivity enhancement as a result of structural transformation from primarily subsistence to more specialized production systems raises the intensity of market participation, which fosters better utilization of resources based on comparative advantage. And in a recent study in Cambodia, Khun and Lim (2022) report that enhanced productivity in rice farming expands the likelihood of market participation. Investigating the relationship between agricultural commercialization and productivity thus requires additional effort to disentangle these potential causal associations.

2.3 The role of farm size

Whether it is through the increased commercialization of food crops or the adoption of cash crops for sale, market participation is expected to have a positive impact on farm productivity and to initiate a virtuous cycle of poverty reduction and welfare improvement (Dione, 1989; Goetz, 1993; Von Braun and Kennedy, 1994; Kelly et al., 1996; Poulton et al., 1998; Dorward et al., 1998). Existing literature, however, has documented considerable variation in farm efficiency and intensity of commercialization across farms of different scales. Production scale may thus play an important role in the direction and magnitude of any observed impacts between crop commercialization and productivity.

Numerous studies on agricultural production efficiency in low-income countries have found a non-constant relationship between farm productivity and scale (Foster and Rosenzweig, 2022; Kimhi, 2006; Muyanga and Jayne, 2019). Foster and Rosenzweig (2022) show that when household labor is fully exploited, small- and medium-scale farmers are often unwilling to hire additional labor due to the existence of fixed transaction costs, even when the hiring is profitable. In contrast as larger farms use labor more intensively, average unit labor costs will vary by operational scale. The outcome is a U-shaped relationship between farm size and productivity where the smallest and largest farms are most efficient in their use of labor while medium-sized farms are least efficient.

Similarly, the intensity of market participation may also be related to production scale. Farm households with more land exhibit a higher propensity to produce surpluses. Osmani and Hossain (2015), exploring the market participation of Bangladeshi farmers, find that the likelihood of commercialization increases in tandem with production scale. Martey et al. (2012), Khun and Lim (2022) and Olwande and Mathenge (2012) similarly observe a positive association between farm size and agricultural commercialization in Ghana, Cambodia, and Kenya, respectively. Although the approaches of these studies are very different, the conclusions are much the same. Larger farms appear to have the ability to boost outputs and thus engage in sales of surplus produce. Households with more land also have a greater ability to allocate their land partly for food crops and partly for cash crop production, further allowing them to engage in output markets (Latt & Nieuwoudt, 1988). In addition, where land can be used as a collateral for credit, larger plots help farmers overcome credit constraints supporting mechanization and adoption of improved technologies to increase production and meet market demand (Olwande and Mathenge, 2012).

Existing studies have generally maintained that while productivity has a U-shaped relationship with farm size, the degree of commercialization is increasing with farm size. The impact of farmers' market participation on productivity is thus to a significant extent interwoven with the existing scale of production. If farms are largely categorized into small and large, ceteris paribus, we would expect a greater positive association between commercialization and productivity among smaller farms as opposed to larger ones. The diminishing effects in relation to farm size is rationalized based on the fact that small farms in low-income countries are relatively productive yet less likely to use technologies due to the subsistence nature of production. Thus, market participation has the potential to bring about the modernization of production processes and increased intensity of input utilization, greatly impacting crop yields among these small-scale farms. On the other hand, large farms are already likely to be more productive, use inputs and other technologies, and also be at least somewhat active in the market, resulting in a relatively smaller expected association between increased commercialization and productivity. In other words, at a low level of farm size and productivity, the positive impact of additional commercialization on productivity is expected to be significant, while at larger scales of production, it is expected to be less important.

III. DATA AND DESCRIPTIVE STATISTICS

3.1 Data

We use two datasets – the Cambodia Inter-Censal Agriculture Survey 2019 (CIAS19) and the Cambodia Agriculture Census in 2013 (CAC13). These are the two large-scale agriculture surveys which were conducted by Cambodia's National Institute of Statistics (NIS) of the Ministry of Planning and the Ministry of Agriculture, Forestry and Fisheries (MAFF). The CAC13 was conducted for the entire country in 2013 while the procedure used in the CIAS19 is a two-stage stratified sampling based on the CAC13 sample. The CIAS19 was conducted between July 2018 and June 2019.

The CIAS19 collects data on households' characteristics, crop cultivation, raising livestock and poultry, and aquaculture and capture fishing operations from a sample of 15,985 agricultural households with 30,221 parcels and home lots in 25 provinces including Banteay Meanchey, Battambang, Kampong Cham, Kampong Chhnang, Kampong Speu, Kampong Thom, Koh Kong, Kampot, Kandal, Kep, Kratie, Mondul Kiri, Otdar Meanchey, Phnom Penh, Preah Sihanouk, Preah Vihear. Prey Veng, Pailin, Pursat, Ratanak Kiri, Svay Rieng, Steng Treng, Siemreap, Thbang Khmum, and Takeo. According to the survey, a holding/household comprises up to 18 members and cultivates up to 16 parcels in addition to home lots.[3] We analyze the data at the household levels. Thus, the plot-level data are aggregated to the household level for the analyses.

We further append the CIAS19 with village level information from the CAC13 to serve as instrumental variables (IV). The CAC13 is the only census of Cambodian agriculture conducted in 2013. Except for those living in urban Phnom Penh, the census includes all households who are cultivating at least 0.03 ha and/or owning at least 2 large livestock and/or three head of small livestock and/or a minimum of 25 poultry. It consists of two modules: the core and the supplementary module. For the purpose of our study, we utilize data from a supplementary module designated as Form G. The questionnaire is administered to 12,639 village leaders to collect village level information on the types of soil, topographical features, calamities/disasters, economic activities, local infrastructure, etc. Specifically, the existence of motorcycles, tricycles, and boats; access to internet, telephones, mobile phones; the distance to the nearest national road; and the existence of public market in the village are used as instrumental variables.[4]

To append village data from the CAC13 to CIAS19, we need to identify the village of the respondents in the CIAS19, which is not made publicly available for the purpose of confidentiality. Upon request, a separate village dataset is provided solely for research purposes. We first added the village indicator to the CIAS19 with corresponding sampling weights. Then, the instrumental

[3] Because an overwhelming majority of the holdings are operated by a household, the word "holdings", "households", and "farmers" are used interchangeably.
[4] We provide the justification for the use of instrumental variables in the method section below.

variables at the village level were appended from the CAC13. We were able to match most villages in the two datasets with the exception of a few cases where the sampling weights did not uniquely identify a village in the CAC13, in which case we opted to drop the observations.

3.2 Household crop commercialization and land productivity by province

From the CIAS19, we calculate the crop yield for all households by using equation (1). In the survey, the quantity of crop harvested, q_{ji}, is taken from the question 'What was the total quantity harvested during the last 12 months?', and the cultivated area, a_{ji}, from the question 'What area was planted? (in hectares)', and the number of harvests, m_{ji}, from the question 'How many harvests did you have for the crop during the last 12 months?'. Most of the plots were harvested once or twice per year, except for 143 non-aromatic paddy plots that were harvested three times. There were also some responses for four harvests and continuous harvest which were dropped from the sample.[5]

We calculate HCCI also from the CIAS19 by using equation (2). The sale quantity, s_{ji}, is taken from the question 'What was the quantity of crop sold?'. This variable was reported in a mixture of tons and kilograms; we address this measurement inconsistency by using the data on prices, total harvest, and the response to the question 'Did your household consume all of crop harvested from the plot?' For instance, if the price is expressed in riels (Cambodian currency) per ton, then the quantity sold should be in tons. In addition, this quantity sold should be in certain proportion to the total harvest reported.[6]

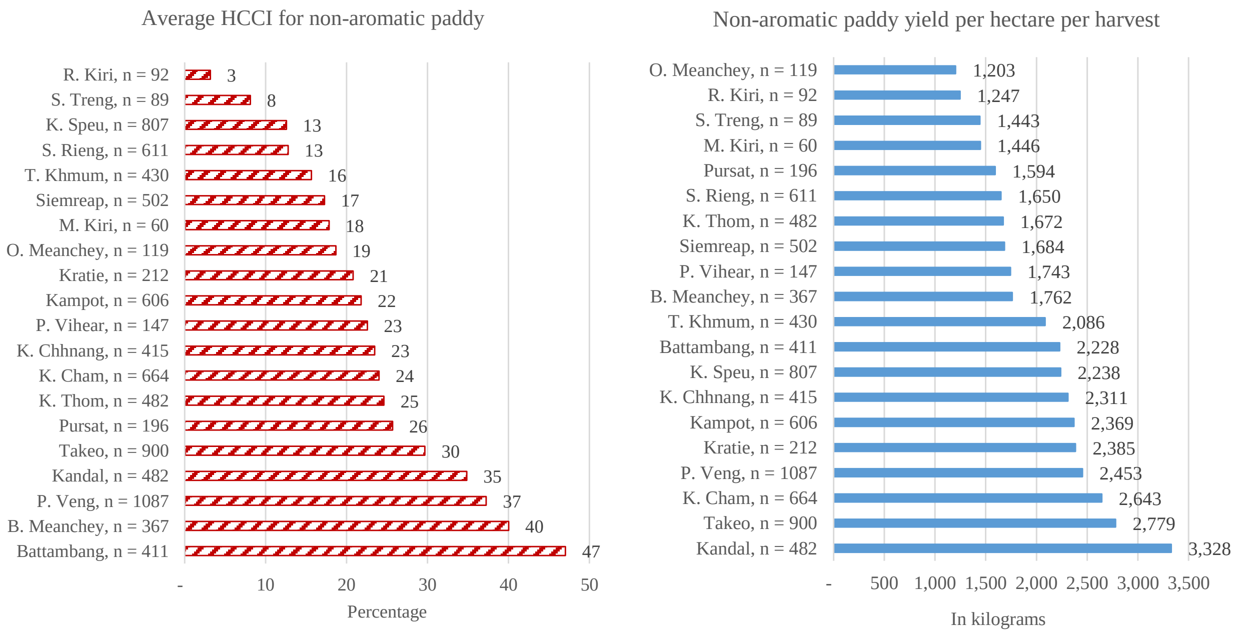
Averages for estimated crop yield and HCCI by crop and household across provinces are reported in Figures 1-4 (major cities including Phnom Penh, Koh Kong, Preah Sihanouk, and Kep as well as one province with only two households are excluded). Figure 1 shows the average non-aromatic paddy yield and household crop commercialization index (HCCI) by province. The average HCCI was 23%, implying that an average Cambodian household sold about 23% of their non-aromatic paddy production. This ranged from as low as 3% in Ratanak Kiri, the second least productive province to as high as 47% in Battambang, the well-known rice producing province of the country with a slightly-above-average productivity. The average yield across 20 provinces in the sample was 2,013 kilograms per hectare per harvest, ranging from as low as 1,203 kilograms in Otdar Meanchey to as high as 3,328 kilograms in Kandal. An average household in Kandal, the most productive province, sold about 35% of their production. Prey Veng and Takeo, the known large rice producing provinces, had an average yield of 2,453 kilograms and 2,779 kilograms and sold about 37% and 30% of their production, respectively.

Figure 2 shows the average aromatic paddy yield and HCCI across 17 provinces growing aromatic paddy in Cambodia.[7] The average HCCI indicated that an average Cambodian household sold about 40% of their aromatic paddy production. The average yield was about 2,180 kilograms per hectare per harvest, slightly higher than that of non-aromatic paddy. Again, Otdar Meanchey was the least productive province with yield at 1,581 kilograms, selling about 29% of its production

[5] There are very few of them across the four crops – 13 observations for non-aromatic paddy, 2 for aromatic paddy, 3 for maize, and 12 for cassava.
[6] The code to sort out this data inconsistency is available upon request.
[7] The data on aromatic paddy appears limited. For reasons unknown to the authors, the survey does not seem to cover the entire country fully, as evidenced by the high-producing province of Kandal having only 3 households surveyed.

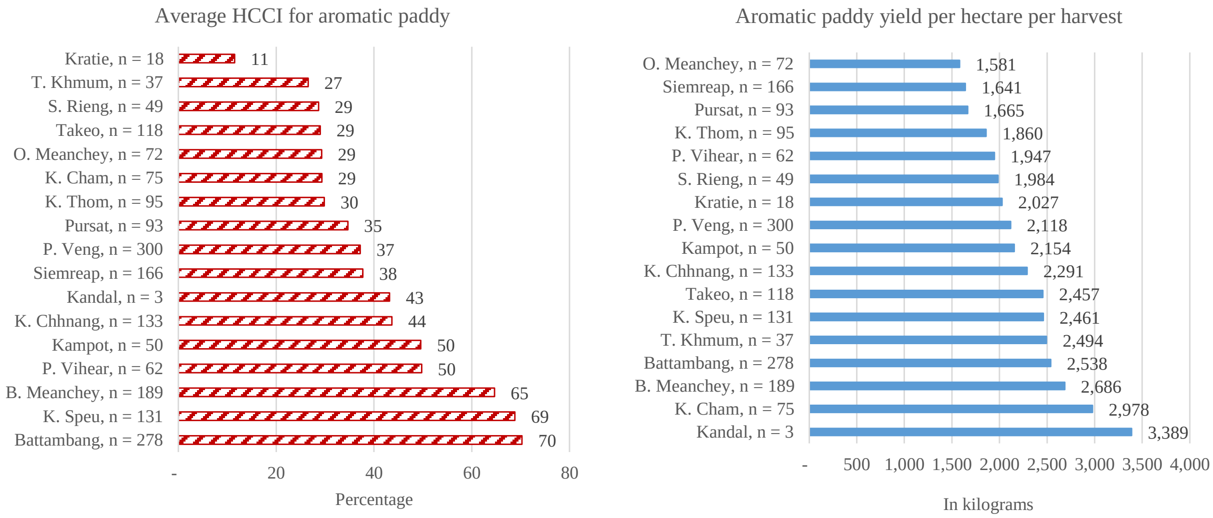
while the most productive province was Kandal with yield at 3,389 kilograms, selling about 43% of its production. This was followed by Kampong Cham, the second most productive province, but it sold an average 29% of its crops. The top three provinces with the highest crop commercialization were Battambang, Kampong Speu, and Banteay Meanchey, which sold over 65% of their production.

Figure 1: Non-aromatic paddy yield and average HCCI by province



Note: The values are the average of all households in the sample by the province. *n* is the sample observations in each province. We drop the major cities such as Phnom Penh, Koh Kong, Preah Sihanouk, and Kep as well as the province with a sample of only two households. Source: Cambodia Inter-Censal Agriculture Survey 2019

Figure 2: Aromatic paddy yield and average HCCI by province

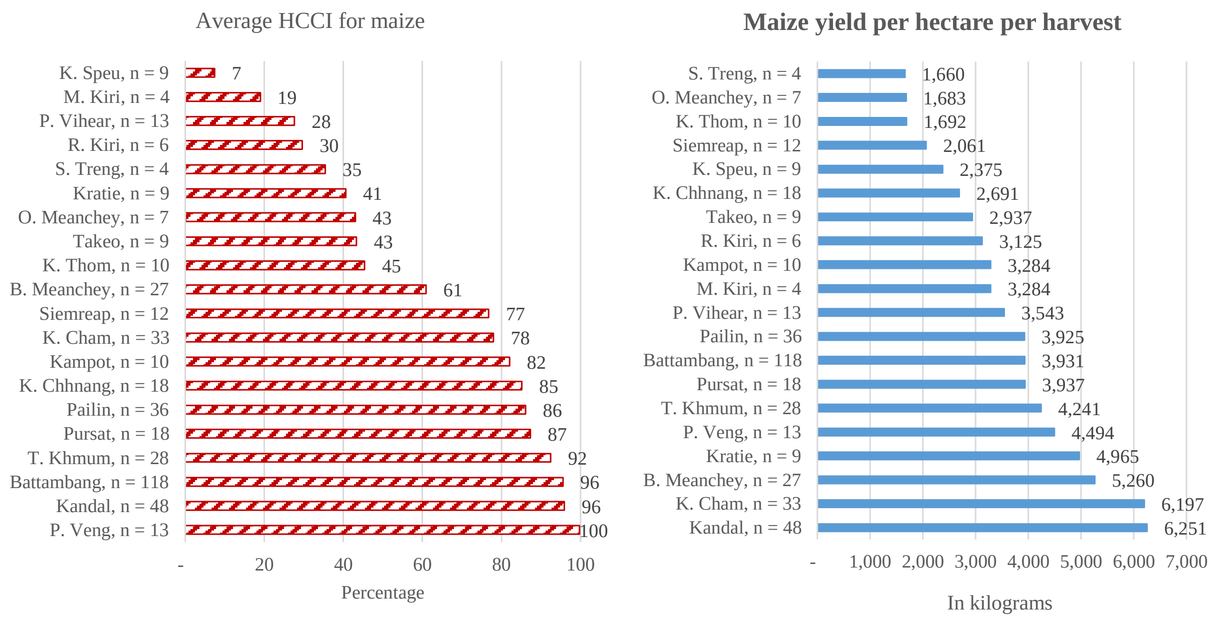


Note: The values are the average of all households in the sample by the province. *n* is the sample observations in each province. We drop the major cities such as Phnom Penh, Koh Kong, Preah Sihanouk, and Kep as well as the province with a sample of only two households. Source: Cambodia Inter-Censal Agriculture Survey 2019

Figure 3 shows the average maize yield and HCCI across 20 maize-growing provinces. Because maize is primarily a cash crop in Cambodia, it is largely commercialized. Households in ten provinces including Siemreap, Kampong Cham, Kampot, Kampong Chhnang, Pailin, Pursat, Thbang Khmum, Battambang, Kandal, and Prey Veng, sold over 75% of their crops. Nonetheless, at the household level, the variation in HCCI is still high. The HCCI within Siemreap varied by 37% on average and that within Kampong Chhnang varied by 32% on average. The household's average maize yield varied significantly from as low as 1,660 kilograms in Steng Treng to 6,251 kilograms in Kandal. Despite their high commercialization, two provinces still suffered from low productivity. Households in Siemreap harvested an average 2,061 kilograms per hectare and those in Kampong Chhnang harvested an average 2,691 kilograms.

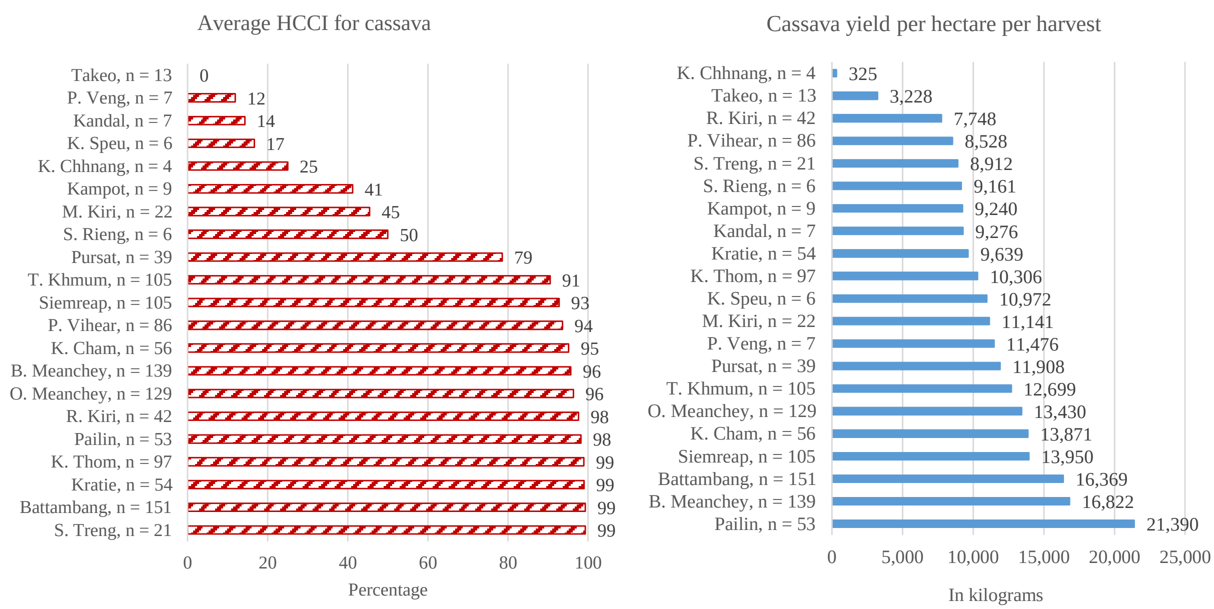
Figure 4 shows the average cassava yield and HCCI in 21 cassava-growing provinces across the country. Like maize, cassava is also a cash crop in Cambodia and thus the HCCI is high in most of the provinces. The average cassava-producing household in twelve of the provinces sold more than 90% of their harvest. Still, there is some variation within the province. For example, in Banteay Meanchey and Kampong Cham HCCI varied by about 20% on average. The average household yield varied significantly from as low as 325 kilograms in Kampong Chhnang to 21,390 kilograms in Pailin. In Takeo, the second least-productive province consisting of only 13 households in the sample, none reported any commercialization of cassava.

Figure 3: Maize yield and average HCCI by province



Note: The values are the average of all households in the sample by the province. *n* is the sample observations in each province. We drop the major cities such as Phnom Penh, Koh Kong, Preah Sihanouk, and Kep as well as the province with a sample of only two households. Source: Cambodia Inter-Censal Agriculture Survey 2019

Figure 4: Cassava yield and average HCCI by province



Note: The values are the average of all households in the sample by the province. *n* is the sample observations in each province. We drop the major cities such as Phnom Penh, Koh Kong, Preah Sihanouk, and Kep as well as the province with a sample of only two households. Source: Cambodia Inter-Censal Agriculture Survey 2019

3.3 Descriptive statistics and correlation matrix

In addition to crop yield and HCCI, we also draw several other variables from the CIAS19 data including agriculture inputs, exposure to shocks, access to agriculture training and agriculture loans, and other farm-household characteristics. The agricultural inputs include fertilizer, pesticide and irrigation, and household characteristics include age, gender, marital status, and education level of the household head. The additional instrumental variables (at the village level) which are drawn from the CAC13 include the existence of motorcycles, tricycles, and boats, access to the internet, telephones or mobile phones, distance to the nearest national road, and the presence of a public market in the village. Descriptive statistics of all variables are reported in Table 1.

Fertilizer, pesticide, and irrigation are binary variables which take a value of 1 if the household uses the input in at least one of the plots and zero, otherwise.[8] In the sample, there were very few households with two plots of the same crop and among them only a few used any inputs in one plot but not the other. Therefore, we consider the household using the input for a crop if they used it in any one of the crop plots.[9]

As shown in Table 1, 88% of households used fertilizers for non-aromatic paddy, and 92% for aromatic paddy, while only about half of households used fertilizers for maize or cassava. On the other hand, 64% of households used pesticides for non-aromatic paddy, 70% for aromatic paddy, 63% for maize, and 55% for cassava. For irrigation, fewer than half of households overall have access to irrigation. In total 45% of households used irrigation for non-aromatic paddy, followed by 43% for aromatic paddy, 32% for maize and only 8% for cassava.

Age, gender, and marital status data reported are those of the household head. The average age of the household head in the sample is 48 years with the youngest being 20 and the oldest 65. Roughly 77% of household heads are male. Education level of the household head is reported in four categories – 21% of household heads have no formal education, 50% have primary education, 20% have secondary education, and 9% have a high school or technical diploma, or tertiary education.

Two additional household-level variables are agricultural trainings and loans. Both are binary. The agricultural training variable is drawn from the question ‘Have you ever received any formal training on agriculture?’ and takes a value of 1 if the household head has received training and zero, otherwise. The data show that only 13% of sample households have received formal training. Access to agricultural loans is measured by two questions ‘Did you or any member of your household have a loan?’ and ‘Was any part of the loan used for agricultural purposes?’. By this metric 26% of sample households have accessed agricultural loans.

The last variable from the CIAS19 is exposure to shocks, a binary variable which is derived from the question ‘Did any severe shocks hit the holding or household in the past 12 months?’ The severe shocks listed include typhoon, floods, landslide, drought, insects, and crop diseases. Approximately 38% of sample households experienced a shock in the past 12 months.

[8] Unfortunately, the amounts of fertilizers and pesticides used in the cultivation is not available in the data.
[9] Of 93 households in the sample who have two plots of non-aromatic paddy, only 25 used fertilizers in one of the plots; 53 used pesticides in one of the plots; and 58 used irrigation in one of the plots while the rest used the inputs in both plots. Of 13 households in the sample who have two plots of aromatic paddy, only 3 used fertilizers in one of the plots; 7 used pesticides in one of the plots; and 8 used irrigation in one of the plots while the rest used the inputs in both plots. Of 5 households who have two plots of maize, none used any inputs in either of the plots. Of 38 households who have two plots of cassava, 21 used fertilizers in one of the plots; 24 used pesticides in one of the plots; and none used irrigation in one of the plots while the rest used the inputs in both plots.

Table 1: Descriptive statistics

Variable	Observations	Mean	Std. dev.	Min	Max
Fertilizer					
Non-aromatic	8,808	0.878	0.327	0	1
Aromatic	1,935	0.922	0.268	0	1
Maize	605	0.590	0.492	0	1
Cassava	1,409	0.520	0.500	0	1
Pesticide					
Non-aromatic	8,808	0.643	0.479	0	1
Aromatic	1,935	0.708	0.455	0	1
Maize	605	0.635	0.482	0	1
Cassava	1,409	0.546	0.498	0	1
Irrigation					
Non-aromatic	8,808	0.448	0.497	0	1
Aromatic	1,935	0.434	0.496	0	1
Maize	605	0.326	0.469	0	1
Cassava	1,409	0.079	0.269	0	1
Trained on agriculture (Trained)	10,942	0.131	0.338	0	1
Agricultural loan (Loan)	10,942	0.260	0.439	0	1
Exposed to shock (Shock)	10,942	0.378	0.485	0	1
Age	10,942	48.393	11.554	20	65
Male	10,942	0.774	0.418	0	1
No education (Edu0)	10,812	0.211	0.408	0	1
Primary education (Edu1)	10,812	0.498	0.500	0	1
Secondary education (Edu2)	10,812	0.200	0.400	0	1
High school and above (Edu3)	10,812	0.091	0.288	0	1
Instrumental variables					
Motorcycle (Moto)	1,073	0.973	0.162	0	1
Tricycle	1,073	0.293	0.455	0	1
Boat	1,073	0.246	0.431	0	1
Internet	1,073	0.094	0.292	0	1
Telephone (Tel)	1,073	0.774	0.419	0	1
Mobile	1,073	0.914	0.280	0	1
Distance to national road (Road)	1,073	8.375	12.525	0	90
Public market (Market)	1,073	0.147	0.355	0	1

Note: The major cities such as Phnom Penh, Koh Kong, Preah Sihanouk, and Kep are dropped.
Sources: Cambodia Inter-Censal Agriculture Survey 2019; Cambodian Agriculture Census 2013

Finally, we employ eight variables at the village level drawn from the CAC13 as instrumental variables for crop commercialization. They represent the infrastructure that has existed in each sampled village in 2013. Three variables measure access to modes of transportation including motorcycles, tricycles, and boats. Motorcycles are found in 97% of villages whereas only 29%

have access to tricycles and 25% have access to boats.[10] Three variables measure access to modes of telecommunication including internet, telephones, and mobile phones. While roughly 9% of sampled villages have access to the internet, over 77% have access to telephone lines and 91% have access to mobile phones. Two final variables measure distance to the nearest national road from the village and the presence of a public market. Of 1,073 villages in the sample, the distance to the national road ranges from 0 to 90 kilometers, averaging about 8 kilometers. Of those villages, only about 15% have a public market.

Table 2 presents the correlation matrix of all variables used in the analyses including instrumental variables. All variables are not highly correlated with one another, clearing the possible problem of multicollinearity.

[10] While there may be concerns about the low variation of the motorcycle variable to be used as an instrument, we also include other means of transportation including tricycles and boats. As we will discuss in the methodology section below, we carry out the Stock-Yogo test for weak instruments to test the validity of the instrumental variables.

Table 2: Correlation matrix

	Yield	HCCI	Fertilizer	Pesticide	Irrigation	Trained	Loan	Shock	Age	Male	Edu0	Edu1	Edu2	Edu3	Moto	Tricycle	Boat	Internet	Tel	Mobile	Road	Market
Yield	1																					
HCCI	0.394*	1																				
Fertilizer	-0.132*	-0.018*	1																			
Pesticide	0.022*	0.188*	0.329*	1																		
Irrigation	-0.090*	0.071*	0.265*	0.314*	1																	
Trained	0.031*	0.063*	-0.014	0.008	0.020*	1																
Loan	0.139*	0.225*	-0.128*	0.015	-0.043*	0.080*	1															
Shock	0.018*	0.085*	-0.031*	0.042*	-0.078*	0.101*	0.153*	1														
Age	-0.019*	-0.034*	0.079*	0.059*	0.069*	0.048*	-0.083*	-0.010	1													
Male	0.060*	0.128*	-0.045*	0.021*	-0.003	0.028*	0.093*	0.013	-0.119*	1												
Edu0	-0.010	-0.062*	-0.088*	-0.079*	-0.079*	-0.069*	-0.017	0.012	0.148*	-0.206*	1											
Edu1	-0.005	0.001	0.014	0.026*	0.024*	0.009	0.022*	0.023*	-0.005	-0.002	-0.522*	1										
Edu2	0.010	0.046*	0.049*	0.036*	0.040*	0.035*	0.008	-0.020*	-0.101*	0.140*	-0.260*	-0.495*	1									
Edu3	0.010	0.026*	0.033*	0.016	0.016	0.034*	-0.026*	-0.030*	-0.063*	0.105*	-0.163*	-0.310*	-0.155*	1								
Moto	0.003	-0.022*	-0.048*	-0.007	-0.051*	-0.009	-0.030*	0.002	0.023*	-0.003	0.018	-0.002	-0.015	-0.002	1							
Tricycle	0.004	-0.018	0.125*	0.140*	0.162*	-0.013	-0.080*	-0.092*	0.056*	-0.010	-0.068*	0.004	0.029*	0.050	0.073*	1						
Boat	-0.037*	0.087*	0.040*	0.153*	0.222*	0.001	0.010	0.036*	0.039*	0.006	-0.031*	0.021*	0.015	-0.011	0.003	0.086*	1					
Internet	-0.024*	-0.021*	0.006	-0.002	0.049*	-0.031*	-0.029*	-0.057*	0.053*	0.006	-0.013	-0.022*	-0.006	0.065*	0.021*	0.112*	0.071*	1				
Tel	-0.060*	-0.093*	-0.008	-0.004	0.003	-0.020*	-0.068*	-0.074*	0.030*	-0.036*	-0.009	-0.027*	0.017	0.035*	0.061*	0.073*	0.114*	0.110*	1			
Mobile	0.025*	0.044*	-0.050*	-0.027*	-0.082*	0.020*	0.026*	-0.017	-0.018	0.008	0.023*	0.004	-0.025*	-0.005	0.173*	-0.014	0.020*	-0.071*	0.163*	1		
Road	0.043*	0.060*	-0.148*	-0.065*	-0.018	0.036*	0.086*	0.038*	-0.051*	0.015	0.057*	0.011	-0.035*	-0.054*	-0.066*	-0.133*	0.081*	-0.012	-0.030*	0.004	1	
Market	0.026*	0.068*	0.003	0.029*	0.005	0.011	0.013	-0.010	0.039*	0.028*	-0.039*	-0.008	0.035*	0.021*	0.027*	0.076*	-0.015	0.220*	0.005	0.037*	-0.099*	1

Note: * denotes significance at the 95% confidence level

IV. EMPIRICAL APPROACH

To examine the impact of household crop commercialization on land productivity, we estimate the following equation:

$$Yield_{hj} = \alpha HCCI_{hj} + \beta X_{hj} + u_{hj} \quad (3)$$

where $Yield_{hj}$ and $HCCI_{hj}$ are described above. X_{hj} is a vector of explanatory variables including exposure to shocks, household characteristics, use of agricultural inputs, crop dummies and other fixed effects. u_{hj} is an error term. We initially run ordinary least square (OLS) regressions with alternative specifications to narrow the list of potential explanatory variables to include in the main analyses.

We provide evidence for the impact of household crop commercialization (HCCI) on land productivity (Yield) in three steps. First, we examine the general evidence by looking at the combined sample of all four crops – non-aromatic and aromatic paddies, maize, and cassava. Then, we examine the relationship for each crop, separately. Finally, we examine the role of farm size in potentially mediating the association between crop commercialization and yield gains by separating the sample into small and large farms.

As described in the conceptual framework, the potential reverse causality between land productivity and crop commercialization, as well as the unobserved factors that may simultaneously affect land productivity and crop commercialization, generate an endogeneity problem. The assumption of independent u_{hj} is thus violated due to the endogeneity of $HCCI_{hj}$. To correct for this, we use a two-stage least-squares method for all regression models. Before estimating equation (3), we first estimate the equation:

$$HCCI_{hjv} = \gamma Z_v + \delta X_{hjv} + e_{hjv} \quad (4)$$

where the variables *HCCI* and *X* are now also identified at the village level as Z_v, a vector of excluded instruments, is at the village level. *Z* includes the measures of infrastructure that has existing within villages as reported in the 2013 Cambodian Agriculture Census (as summarized in Table 1). For the instruments to be valid, they must be strongly correlated with *HCCI* but not directly related to land productivity, except through its impacts on *HCCI* (Fuller, 1977; Stock and Yogo, 2005). Thus, we employ the Fuller 1 approach for instrumental variable (IV) estimation (see Fuller, 1977), which provides a bias-corrected limited information maximum likelihood estimator. The approach provides two important tests, the Stock-Yogo test for weak instruments and the Hansen test of overidentification restrictions. The former is to test if the instruments are potentially weak.[11] The Hansen test seeks to confirm the instruments are not correlated with the error term, u_{hj}.[12]

In a final set of analyses, we employ a similar IV approach to explore the potential channels through which household crop commercialization might plausibly affect crop yield. Specifically,

[11] The null of weak instruments is rejected if the Kleibergen-Paap (K-P) *F*-statistic for the excluded instruments is larger than the Stock-Yogo (S-Y) critical value(s) at a 5% significance level for tests of both 30% and 5% maximal Fuller relative bias.

[12] For this test, the Hansen *J*-statistic and its *p*-value are provided.

we consider the degree to which HCCI is associated with use of potential productivity-enhancing inputs drawn from the review of literature including use of fertilizer, pesticides, or irrigation, as well as accessing trainings on agriculture, and receiving an agricultural loan. In these final regression models, because all outcome variables are binary, we use Probit regressions. In all cases, there is also still a possibility that HCCI is endogenous – therefore, we employ both IV Probit and IV Fuller 1 approaches, using the Wald test of exogeneity to determine if HCCI is exogenous. Where HCCI is found to be exogenous, the Probit estimation without instruments is employed. If it is not exogenous, the IV Fuller 1 estimation is employed. As before, the IV Fuller 1 approach gives the Kleibergen-Paap statistic to test the weakness of the instruments and the Hansen statistic to test the overidentification restrictions.

V. RESULTS

5.1 Crop commercialization and yield for all crops

Equation (3) is estimated with several control variables including shock, age, age squared, male, primary education, secondary education, high school and above, fertilizer, pesticide, irrigation, agriculture training, and agriculture loan. The preliminary OLS estimation result provided in Column 1 of Table 3 shows that household crop commercialization is positively associated with overall crop yield and the association is statistically significant at the 99% confidence level. It also shows that the yield of crops in households that experience shocks are significantly lower, while household use of fertilizer or irrigation, and access to training, are all positively associated with crop yield. There are no significant differences in yield among households that use or do not use pesticides, or among households with or without agricultural loans.

It is possible that the use of pesticides and obtaining agriculture loans are the channels through which crop commercialization affects land productivity. As we discussed in the conceptual framework above, the movement from subsistence to commercialization encourages specialization and efficiency. The farmers that increasingly sell their crops will more likely employ mechanized equipment and use pesticides to improve yield. They may take out agricultural loans to add more capital to the farms. To test this possibility, we drop HCCI from the equation, with the results in Column 2 showing that the coefficient of pesticides now becomes statistically significant at the 99% confidence interval, indicating that the plots that use pesticides yield 216 kilograms per hectare per harvest more than the ones that do not. While the coefficients of fertilizer, irrigation, and agriculture training become more important in both the magnitudes and the significance level, the coefficient of agricultural loans remains insignificant. That may imply that agricultural loans are used to purchase those inputs and thus it should not be included in the same equation.

As indicated in the methodology section, the OLS estimates can produce a biased estimate for the impact of HCCI on yield due to the potential endogeneity issue. Thus, we employ an IV Fuller 1 approach to correct for this potential problem. Findings in Column 3 indicate that there is a significant impact of crop commercialization on land productivity. The effect is also economically large. On average, a 10-percentage-point increase in the percent of sales for a crop increases the land productivity for that crop by about 300 kilograms per hectare per harvest. For example, these findings suggest that if Battambang, a well-known rice-producing province, can increase sales from 47% to 57% of its non-aromatic rice crop, the rice yield might increase from 2,228 to 2,500 kilograms per hectare per harvest. For the bottom two provinces, Ratanak Kiri and Steng Treng, which, respectively, sold only 3% and 8% of their non-aromatic rice crops, yields could reach roughly 2,500 kilograms per hectare if the households could only sell the same share of their non-aromatic harvest as Battambang does presently.

The instrumental variables included in the regression models pass both the weak identification and overidentification tests. The Kleibergen-Paap *F*-statistic is 22.9, which well exceeds the Stock-Yogo critical values at the 5% significance level of 5.02 and 3.33 based on a 5% and 30% maximal Fuller relative bias. That is, the instruments that are used are strongly correlated with HCCI. The Hansen *J*-statistic of 10.08 is associated with a *p*-value of 12%, failing to reject the null that the instruments are not correlated with the error term.

In addition to the result on the effect of HCCI on yield, we should note some other interesting findings from Column 3. While the impact of shocks to the household remains large and significant, the coefficients on other household characteristics appear more important. Younger household heads appear to be more productive, on average. However, the relationship is non-linear, indicating that productivity decreases with age, but at a slower rate. The results also suggest female household heads are more productive than their male counterparts after accounting for other factors.

The coefficients on agricultural inputs such as fertilizer, pesticide, irrigation, and agriculture loans appear negative or insignificant after accounting for HCCI, except for that of training which remains statistically significant, though the magnitude falls by almost one third in the full model. This again suggests that HCCI might affect yield through its impacts on using fertilizer, pesticide, and irrigation as well as obtaining training and agriculture loans. In Column 4 of Table 3, we drop all input variables except training and the results remains qualitatively and quantitatively similar.

Next, we examine the channels through which HCCI might affect yield by regressing individual agricultural inputs including fertilizer, pesticide, and irrigation as well as training and agricultural loans on HCCI. The results are presented in Table 4. The coefficient of HCCI is positive and statistically significant in all regressions, suggesting that household crop commercialization enables farmers to specialize and improve efficiency by adopting the use of fertilizers, pesticides, and irrigation, and by obtaining training and agricultural loans in order to do so. Statistically, it should be noted that the Wald test of exogeneity is rejected in three regressions including fertilizer, pesticide, and irrigation. Thus, the IV Fuller 1 is estimated, and the results pass both the weak identification and overidentification restriction tests, indicating the instruments are strongly related with HCCI and are not correlated with the error term. The Wald test fails to reject the null of exogenous HCCI for agricultural training and loans. Thus, the Probit estimation is used.

Table 3: Household crop commercialization and land productivity (all crops)

Variable	(1) OLS	(2) OLS	(3) IV Fuller 1	(4) IV Fuller 1
	Dependent variable: Yield			
HCCI	8.075***	-	31.28***	29.67***
	(0.851)		(7.625)	(5.403)
Shock	-386.5***	-400.2***	-350.4***	-351.5***
	(67.97)	(68.10)	(78.57)	(74.99)
Age	-27.91	-22.20	-60.56**	-66.14**
	(25.84)	(25.84)	(30.72)	(29.90)
Age squared	0.310	0.246	0.656**	0.713**
	(0.274)	(0.274)	(0.328)	(0.321)
Male	-5.340	40.13	-167.7**	-188.5**
	(63.79)	(63.68)	(80.23)	(80.73)
Primary education	32.97	46.99	-43.68	-
	(76.99)	(77.26)	(86.59)	
Secondary education	128.7	165.1*	-33.36	-
	(90.01)	(90.21)	(109.8)	
High school and above	195.0	240.7*	74.61	-
	(125.7)	(125.2)	(138.8)	
Fertilizer	264.7*	331.1**	126.7	-
	(150.5)	(150.9)	(172.3)	
Pesticide	123.75	216.5***	-254.5**	-
	(82.57)	(82.27)	(127.9)	
Irrigation	162.3***	239.4***	-57.15	-
	(52.39)	(51.70)	(82.93)	
Trained on agriculture	309.49***	325.7***	238.1**	222.8**
	(95.36)	(95.34)	(101.5)	(100.8)
Agricultural loan	38.36	118.7	-198.5	-
	(74.66)	(74.15)	(124.7)	
Constant	2,756***	2,108***	8,058***	7,821***
	(607.7)	(598.5)	(1,041)	(1,023)
Province dummies	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes
Weak identification test				
Kleibergen-Paap (K-P) *F*-statistic	-	-	22.90	33.96
Stock-Yogo (S-Y) critical value(s)				
5% maximal Fuller relative bias	-	-	5.02	5.02
30% maximal Fuller relative bias	-	-	3.33	3.33
Overidentification test				
Hansen *J*-statistic	-	-	10.08	8.69
p-value	-	-	0.121	0.192
Observations	11,861	11,861	9,825	9,941
R-squared	0.539	0.536	-	-

Note: Robust standard errors are reported in parentheses. The instruments for IV Fuller 1 include Tricycle, Boat, Internet, Telephone, Mobile, Road, and Market. For the weak identification test, the null of weak instruments is rejected in the case that the Kleibergen–Paap *F*-statistic on the excluded instruments exceeds the Stock-Yogo critical value(s) at the 5% significance level. Hansen *J*-statistic and *p*-value are also reported for the test of overidentification. The null hypothesis is that the instruments are not correlated with the error term. *** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

Table 4: Channels for the effect of household crop commercialization on land productivity (all crops)

Variable	Fertilizer		Pesticide		Irrigation		Trained on agriculture		Agricultural loan	
	(1) IV Probit	(2) IV Fuller 1	(3) IV Probit	(4) IV Fuller 1	(5) IV Probit	(6) IV Fuller 1	(7) IV Probit	(8) Probit	(9) IV Probit	(10) Probit
HCCI	0.019***	0.002***	0.027***	0.010***	0.028***	0.016***	0.006**	0.002***	0.009***	0.006***
	(0.003)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.0004)	(0.0025)	(0.0004)
Constant	0.116	0.625***	-0.371**	0.436***	-1.985***	-0.372***	-1.335***	-1.432***	-1.039***	-0,726***
	(0.205)	(0.059)	(0.157)	(0.065)	(0.257)	(0.068)	(0.203)	(0.074)	(0.173)	(0.056)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	Motorcycle, Boat, and Market		Boat and Market		Motorcycle, Boat, and Market		Boat, Telephone, Mobile, and Market	-	Boat, Internet, Telephone, Market	-
Weak identification test										
K-P *F*-stat.	-	65.78	-	96.13	-	65.78	-	-	-	-
S-Y critical values:										
5% max. Fuller bias	-	9.61	-	13.46	-	9.61	-	-	-	-
30% max. Fuller bias	-	5.60	-	7.49	-	5.60				
Overidentification test										
Hansen *J*-stat.	-	2.28	-	0.12	-	3.04	-	-	-	-
p-value	-	0.319	-	0.730	-	0.219	-	-	-	-
Wald test of exogeneity										
Chi-squared stat.	9.26	-	102.3	-	229.0	-	1.74	-	1.43	-
p-value	0.002	-	0.000	-	0.000	-	0.187	-	0.232	-
Observations	9,941	9,941	9,941	9,941	9,941	9,941	9,941	11,997	9,941	11,997

Note: Robust standard errors are reported in parentheses. For the weak identification test, the null of weak instruments is rejected in the case that the Kleibergen–Paap (K-P) *F*-statistic on the excluded instruments exceeds the Stock-Yogo (S-Y) critical value(s) at the 5% significance level. Hansen *J*-statistic and *p*-value are also reported for the test of overidentification. The null hypothesis is that the instruments are not correlated with the error term. The null hypothesis for the Wald test is that the instrumented variable is exogenous. *** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

5.2 Crop commercialization and yield by crop

We have provided evidence for the impact of crop commercialization on overall land productivity and the channels through which productivity impacts take place. Our next step is to examine patterns for each crop separately. Before we look at the results from each crop, we should note that among the four crops in the sample, non-aromatic paddy has the largest sample size, consisting of 8,808 households, followed aromatic paddy with 1,935 households, cassava with 1,409 households, and maize with only 605 households.

Table 5 shows the results for non-aromatic paddy, which are quite consistent with those obtained from the full sample combining all crops. This may be expected since non-aromatic paddy contains the majority of the full sample. The magnitude of the impact of HCCI on yield is slightly larger here than in the full sample, suggesting that an increase in commercialization of non-aromatic rice by additional 10 percentage points is associated with an increase in yield of on average 330 kilograms per hectare. The subsequent regressions for hypothesized impact channels (i.e., use of inputs) suggests productivity gains occur through farmer investment in the use of fertilizers, pesticides, and irrigation as well as acquiring new knowledge from training and obtaining loans for farming equipment and other inputs.

For aromatic paddy, because none of the instruments pass the weak identification test, we estimate the impact of HCCI on aromatic paddy yield with the OLS approach. The results are shown in Table 6. Although the impact of HCCI on yield is positive and statistically significant at the 99% confidence level, the magnitude is relatively small. A 10-point increase in the sale share of aromatic rice only raises land productivity by about 50 kilograms per hectare. Among other variables in the model the education of the household head also matters for productivity: those with at least primary school education are more productive than those with no formal education. For the channels through which productivity impacts occur, the effects of HCCI on pesticide and irrigation use for aromatic paddy are compatible with those estimated for non-aromatic paddy, but the impacts on the use of fertilizer and agricultural loans are much lower. However, the latter may not be comparable at all because the estimates for aromatic paddy are obtained from simple Probit estimation rather than the IV Probit estimation used for the non-aromatic paddy. We suspect that these results may suffer from a representative sample size problem – that is, the sample for aromatic paddy may be too small to represent the population.

Similar to the case of aromatic paddy, the instruments used do not pass the weak identification test when we examine the causal impact of HCCI on yield for maize and cassava. Thus, the OLS regression results are presented. Table 7 reports the results for maize. The coefficient of HCCI is positive and statistically significant at the 90% confidence interval, indicating that a 10-point increase in the sales share of maize is associated with an increase in maize productivity of about 120 kilograms per hectare. This magnitude is only about half that observed in the full sample for all crops. The results also show that the impact occurs as farmers are more likely use pesticides, irrigation, and agricultural loan. Table 8 reports results for cassava. The coefficient of HCCI is positive and somewhat comparable to that obtained in the full sample. Increasing cassava commercialization by 10 percentage points is associated with an increase in productivity by over 230 kilograms per hectare, with impact pathways including increased use of fertilizers, irrigation, and agricultural loans.

Table 5: The effects of household commercialization of non-aromatic paddy

Variable	Yield (1) IV Fuller 1	Fertilizer (2) IV Probit	Pesticide (3) IV Probit	Irrigation (4) IV Probit	Trained on agriculture (5) Probit	Agriculture loan (6) IV Probit
HCCI	33.02***	0.019***	0.026***	0.027***	0.003***	0.013***
	(2.666)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
Shock	-180.9***	-	-	-	-	-
	(40.06)					
Age	-38.30**	-	-	-	-	-
	(16.61)					
Age squared	0.418**	-	-	-	-	-
	(0.176)					
Male	-148.0***	-	-	-	-	-
	(45.24)					
Constant	1,747***	-0.000	-0.372***	-0.000	-1.560***	-0.000
	(523.9)	(0.830)	(0.068)	(0.611)	(0.095)	(0.874)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	Motorcycle, Boat, Internet, Telephone, Mobile, and Market	Motorcycle, Boat, and Market	Motorcycle, Boat, and Market	Motorcycle, Boat, and Market	-	Motorcycle, Boat, Mobile, Road, Market
Weak identification test						
K-P *F*-stat.	43.36	-	-	-	-	-
S-Y critical values:						
5% max. Fuller bias	5.61	-	-	-	-	-
30% max. Fuller bias	3.63	-	-	-		
Overidentification test						
Hansen *J*-stat.	6.54	-	-	-	-	-
p-value	0.257	-	-	-	-	-
Wald test of exogeneity						
Chi-squared stat.	-	8.83	63.32	165.2	-	3.93
p-value	-	0.003	0.000	0.000	-	0.047
Observations	7,084	7,084	7,084	6,967	8,590	7,084

Note: Robust standard errors are reported in parentheses. For the weak identification test, the null of weak instruments is rejected in the case that the Kleibergen–Paap (K-P) *F*-statistic on the excluded instruments exceeds the Stock-Yogo (S-Y) critical value(s) at the 5% significance level. Hansen *J*-statistic and *p*-value are also reported for the test of overidentification. The null hypothesis is that the instruments are not correlated with the error term. The null hypothesis for the Wald test is that the instrumented variable is exogenous. *** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

Table 6: The effects of household commercialization of aromatic paddy

Variable	Yield (1) OLS	Fertilizer (2) Probit	Pesticide (3) IV Probit	Irrigation (4) IV Probit	Trained on agriculture (5) Probit	Agriculture loan (6) Probit
HCCI	5.351***	0.009***	0.029***	0.028***	0.0002	0.003***
	(0.815)	(0.002)	(0.001)	(0.0004)	(0.001)	(0.001)
Shock	-291.8***	-	-	-	-	-
	(67.06)					
Primary education	273.5***	-	-	-	-	-
	(72.76)					
Secondary education	282.7***	-	-	-	-	-
	(85.65)					
High school and above	166.0*	-	-	-	-	-
	(99.23)					
Constant	1,459***	1.450***	-0.915***	-1.109	-0.992***	-0.466**
	(78.68)	(0.343)	(0.151)	(0.268)	(0.249)	(0.212)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	-	-	Boat and Market	Motorcycle, Boat, and Market	-	-
Wald test of exogeneity						
Chi-squared stat.	-	-	6.80	9.52	-	-
p-value	-	-	0.009	0.002	-	-
Observations	1,841	1,804	1,629	1,632	1,858	1,856

Note: Robust standard errors are reported in the parenthesis. The null hypothesis for the Wald test is that the instrumented variable is exogenous.
*** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

Table 7: The effects of household commercialization of maize

Variable	Yield (1) OLS	Fertilizer (2) Probit	Pesticide (3) Probit	Irrigation (4) IV Probit	Trained on agriculture (5) Probit	Agriculture loan (6) IV Probit
HCCI	12.12*	0.002	0.007***	0.034***	-0.002	0.031***
	(6.629)	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)
Constant	3,054	1.078***	0.296	-0.656	-1.571***	-2.722***
	(2,507)	(0.404)	(0.353)	(0.315)	(0.497)	(0.454)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	-	-	-	Motorcycle, Boat, and Market	-	Motorcycle, Boat, Road, and Market
Wald test of exogeneity						
Chi-squared stat.	-	-	-	2.67	-	4.29
p-value	-	-	-	0.102	-	0.038
Observations	428	367	396	299	412	347

Note: Robust standard errors are reported in parentheses. The null hypothesis for the Wald test is that the instrumented variable is exogenous.
*** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

Table 8: The effects of household commercialization of cassava

Variable	Yield (1) OLS	Fertilizer (2) Probit	Pesticide (3) Probit	Irrigation (4) IV Probit	Trained on agriculture (5) Probit	Agriculture loan (6) IV Probit
HCCI	23.82*	0.004*	0.002	0.042***	0.003	0.050***
	(14.03)	(0.002)	(0.002)	(0.008)	(0.002)	(0.005)
Shock	-1,709***	-	-			
	(583.7)					
Constant	1,012	-0.102	0.006	-4.832***	-1.326***	-4.935***
	(715.2)	(0.219)	(0.209)	(0.357)	(0.256)	(0.470)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	-	-	-	Motorcycle, Boat, Road and Market	-	Motorcycle, Boat, and Market
Wald test of exogeneity						
Chi-squared stat.	-	-	-	4.80	-	4.04
p-value	-	-	-	0.028	-	0.044
Observations	1,117	1,117	1,088	725	1,098	868

Note: Robust standard errors are reported in parentheses. The null hypothesis for the Wald test is that the instrumented variable is exogenous.
*** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

Table 9: Non-aromatic paddy smallholders (Area < 1 hectare)

Variable	Yield (1) IV Fuller 1	Fertilizer (2) IV Probit	Pesticide (3) IV Probit	Irrigation (4) IV Probit	Trained on agriculture (5) Probit	Agriculture loan (6) IV Probit
HCCI	49.66***	0.030***	0.037***	0.041***	0.004***	0.028***
	(10.39)	(0.008)	(0.003)	(0.002)	(0.001)	(0.009)
Shock	29.68	-	-	-	-	-
	(70.95)					
Age	-36.87	-	-	-	-	-
	(24.81)					
Age squared	0.417	-	-	-	-	-
	(0.263)					
Male	8.677	-	-	-	-	-
	(67.54)					
Constant	3,512**	1.645***	-0.344	-0.105	-1.625***	-0.514
	(1,642)	(0.368)	(0.455)	(0.081)	(0.128)	(0.397)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	Motorcycle, Boat, Internet, Telephone, Mobile, and Market	Motorcycle, Boat, and Market	Motorcycle, Boat, and Market	Motorcycle, Boat, and Market	-	Motorcycle, Boat, Mobile, Road, Market
Weak identification test						
K-P *F*-stat.	7.47	-	-	-	-	-
S-Y critical values:						
5% max. Fuller bias	5.61	-	-	-	-	-
30% max. Fuller bias	3.63	-	-	-		
Overidentification test						
Hansen *J*-stat.	8.24	-	-	-	-	-
p-value	0.143	-	-	-	-	-
Wald test of exogeneity						
Chi-squared stat.	-	4.46	23.72	57.79	-	3.79
p-value	-	0.035	0.000	0.000	-	0.051
Observations	3,099	3,041	3,084	3,067	3,876	3,096

Note: Robust standard errors are reported in parentheses. For the weak identification test, the null of weak instruments is rejected in the case that the Kleibergen–Paap (K-P) *F*-statistic on the excluded instruments exceeds the Stock-Yogo (S-Y) critical value(s) at the 5% significance level. Hansen *J*-statistic and *p*-value are also reported for the test of overidentification. The null hypothesis is that the instruments are not correlated with the error term. The null hypothesis for the Wald test is that the instrumented variable is exogenous. *** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

Table 10: Non-aromatic paddy large holders (Area ≥ 1 hectare)

Variable	Yield	Fertilizer	Pesticide	Irrigation	Trained on agriculture	Agriculture loan
	(1) IV Fuller 1	(2) IV Probit	(3) IV Probit	(4) IV Probit	(5) Probit	(6) Probit
HCCI	40.48***	0.020***	0.025***	0.026***	0.002***	0.006***
	(3.43)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Shock	-232.1***	-	-	-	-	-
	(49.31)					
Age	24.49	-	-	-	-	-
	(21.66)					
Age squared	-0.220	-	-	-	-	-
	(0.229)					
Male	-61.42	-	-	-	-	-
	(55.34)					
Constant	137.7	-0.000***	-0.000***	-0.000***	-1.451***	-0.597
	(615.6)	(0.815)	(0.692)	(0.622)	(0.142)	(0.103)
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes
Excluded instruments	Motorcycle, Boat, Internet, Telephone, Mobile, and Market	Motorcycle, Boat, and Market	Motorcycle, Boat, and Market	Motorcycle, Boat, and Market	-	-
Weak identification test						
K-P *F*-stat.	27.26	-	-	-	-	-
S-Y critical values:						
5% max. Fuller bias	5.61	-	-	-	-	-
30% max. Fuller bias	3.63	-	-	-		
Overidentification test						
Hansen *J*-stat.	5.99	-	-	-	-	-
p-value	0.31	-	-	-	-	-
Wald test of exogeneity						
Chi-squared stat.	-	5.66	44.79	91.61	-	-
p-value	-	0.017	0.000	0.000	-	-
Observations	3,985	3,717	3,985	3,823	4,700	4,702

Note: Robust standard errors are reported in parentheses. For the weak identification test, the null of weak instruments is rejected in the case that the Kleibergen–Paap (K-P) *F*-statistic on the excluded instruments exceeds the Stock-Yogo (S-Y) critical value(s) at the 5% significance level. Hansen *J*-statistic and *p*-value are also reported for the test of overidentification. The null hypothesis is that the instruments are not correlated with the error term. The null hypothesis for the Wald test is that the instrumented variable is exogenous. *** denotes significance at the 99% confidence level, ** at the 95% level, and * at the 90% level.

5.3 Crop commercialization and yield across small and large farms

Finally, we examine the role of the farm size in potentially mediating the effect of crop commercialization on yield. We expect a greater positive impact of commercialization among small farms than large ones. Because the results are less robust for aromatic paddy, maize, and cassava and the sample sizes of these three crops are relatively small, we choose to only look at non-aromatic paddy for evaluating the potential role of farm size. We define smallholder farmers as those who possess areas of less than one hectare of land and large holders as those with areas of at least one hectare of land. This definition of smallholder farmers in Cambodia is consistent with Eliste and Zorya (2015).

The results for non-aromatic paddy yield as a function of HCCI among smallholder and large holder farmers are reported in Tables 9 and 10, respectively. The coefficients for the impact of HCCI on yield are positive and statistically significant among both groups. Moreover, as expected the coefficient for smallholders is larger than that for relatively larger farms (Column 1 of Table 9 versus Column 1 of Table 10). Similarly, the results for the channels through which HCCI affects yield also show that the impacts of HCCI on use of fertilizer, pesticide, irrigation, training on agriculture, and agricultural loans are greater among smallholder farmers than among large holders, indicating diminishing effects in relation to farm size. However, the Wald tests fail to reject the null hypotheses that the coefficients for the effects of HCCI in the two samples are equal. We examined alternative cut-off points at 0.5 hectares, 2 hectares, and 3 hectares, but results remain unchanged.[13] These null findings could be due the fact that the majority of the observations can be classified as smallholder farmers with less than 5 hectares of land – the number of households that possess at least 5 hectares of land include only about 6% of total observations.

VI. CONCLUSION

In this study, we examine the impact of household crop commercialization on land productivity in Cambodia. Specifically, we look at Cambodian farmers who cultivate non-aromatic paddy, aromatic paddy, maize, and cassava, to see if an increase in commercialization of these crops is associated with improved land productivity, and the input use channels through which productivity gains might take place. We seek to correct for possible endogeneity by using an instrumental variable (IV) estimation, leveraging a combination of data sources from the Cambodia Inter-censal Agriculture Survey 2019 (CIAS19) and the Cambodia Agriculture Census in 2013 (CAC13).

Findings suggest that the impact of crop commercialization on land productivity is economically sizeable. On average a 10-percentage-point increase in crop commercialization is associated with an increase in overall crop yields of roughly 300 kilograms per hectare per harvest. Further analyses of potential impact pathways suggest yield gains may be possible because farmers who commercialize their crops are more likely to use fertilizers, pesticides, and irrigation. They are also more likely to obtain training and acquire agricultural loans to support their farm activities and improve land productivity.

When we examine each crop separately, the results are consistent, both qualitatively and quantitatively, for non-aromatic paddy. Evidence for aromatic paddy, maize, and cassava is also qualitatively consistent – though the estimates are smaller than what is suggested from the all-crop

[13] The results for the Wald tests and regressions at different cut-off points are not reported, but available upon request.

sample, the results continue to support the hypothesis of a causal impact of crop commercialization on yield. Among all the channels investigated, the results indicate that increased use of irrigation and access to agricultural loans are consistently important pathways by which crop commercialization allows farmers to improve their land productivity.

The four crops studied in this analysis together represent over 80% of total agricultural production in Cambodia. As many of the poorest Cambodians are farmers experiencing low productivity, findings suggest that government policy seeking to alleviate poverty and enhance productivity and food security should focus on enhancing commercialization opportunities, enabling farmers to shift from subsistence to more market-oriented farming, in addition to enhancing farmers' access to agricultural inputs including fertilizers, pesticides, and most importantly irrigation and agricultural loans.

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