JICA Ogata Sadako Research Institute for Peace and Development

JICA Ogata Research Institute Working Paper

An empirical analysis on expanding rice production in Sub Sahara Africa

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No. 220

March 2021

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An Inquiry into the Process of Upgrading Rice Milling Service:
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Abstract

Countries in sub-Sahara Africa (SSA) heavily rely on rice imported from Asia, partly because of rapidly increasing rice demand and partly because of consumers' preference for high-quality Asian rice. A few entrepreneurial rice millers in Kenya adopted large-scale improved milling machines, including the component called destoners, around 2010, which they learned from China. Later, smaller-sized improved machines were introduced and more widely adopted. These adopters successfully improved the quality of milled rice, which can compete with imported rice, and their business performance. In contrast, many other millers without adopting improved machines were forced to reduce their business or exit the industry.

Keywords: rice quality, rice milling, destoner, Kenya, sub-Sahara Africa

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* This paper is a result of a research project being conducted at Japan International Cooperation Agency – Ogata Sadako Research Institute for Peace and Development (JICA Ogata Research Institute), entitled "An empirical analysis on expanding rice production in Sub Sahara Africa." The authors are deeply indebted to Etsuko Masuko and Sachiko Mitsumori of JICA Ogata Research Institute for supporting the research project. They also thank Takeshi Sakurai, Kazushi Takahashi, Yuko Nakano, Koji Makino and Kei Kajisa for their valuable comments on earlier versions of this paper. We are grateful for the financial support of JICA Ogata Research Institute, Grant-in-Aid for Scientific Research on Innovative Areas-25101001 and Grant-in-Aid for Scientific Research (A)-17H00986. The authors remain solely responsible for the contents of this paper.
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1. Introduction

Countries in sub-Sahara Africa (SSA) have made serious efforts to increase domestic staple food production to improve food security and facilitate poverty reduction, especially after the 2007-08 food crisis. Meanwhile, rice is found to be a particularly promising crop to increase food production in SSA (Otsuka and Larson 2012, 2016; CARD, 2019; Otsuka, 2019). In fact, the annual growth rate of rice production was as high as 6.8 % between 2009 and 2019 (Soullier *et al*., 2020). However, rice import is estimated to be increasing more rapidly at 7.8 % per annum, and around one-third of rice consumed in SSA is still imported from Asia, with varying degrees in various countries ranging from 10% to 93% (Mendez del Villar and Lançon, 2015; Saito *et al*., 2015; FAO, 2018).

Population growth, urbanization, and increasing income raise rice consumption, and, importantly, urban consumers generally prefer high-quality imported Asian rice over domestic rice (Diako *et al*. 2010; Futakuchi *et al*. 2013; Demont *et al*. 2017; Ibrahim *et al*. 2020). Among many factors affecting grain quality such as varieties, cultivation, harvesting, threshing, and storage technologies (Futakuchi, et al., 2013), it is commonly argued that the use of inappropriate milling machines is a major reason why domestic milled rice cannot compete with imported rice from Asia (Fiamore, *et al*., 2017; Ragasa, *et al*., 2020). Research based on a framed field experiment demonstrates that urban consumers are more willing to purchase rice with high levels of cleanliness and low breakage rates of grains (Demont and Ndour, 2015; Demont *et al*., 2017), which suggests the importance of appropriate rice milling. Importantly, case studies by Tokida *et al*. (2014) and Kapalata and Sakurai (2020) reveal that the adoption of destoners and other improved milling machines allows rice millers to charge higher milling fees and increases their profitability in Uganda and Tanzania, respectively. However, the evidence is still limited whether improved milling technologies enables domestic rice to compete with imported rice.

This paper studies the development process of rice milling cluster in the largest rice production area in Kenya, called the Mwea irrigation scheme, which is situated 90 km northeast of Nairobi, with 8,500 hectares of irrigated paddy area, growing primarily improved Basmati rice,[1] and achieving rice yield of 6.2 tons per hectare with two crop cycles (Njeru *et al*. 2016; Kikuchi, *et al*., 2021). Some of these rice millers have gradually adopted improved milling machines over the past 10 years,[2] and the rice milled by these millers is of higher quality and successfully competes with imported rice from Asia in urban markets, including Nairobi, the capital of Kenya. We observed supermarkets in Nairobi selling the improved Basmati rice from Mwea at 140 to 200 Kshs per kg, compared with Pakistani long grain at 100 to 120 Kshs per kg as of 11 December 2018.[3] These observations indicate that African rice can compete with Asian rice if improved milling machines are introduced to SSA.

We collected the primary data of the commercial millers operating in Mwea in 2011, 2016, 2018, and 2019 to analyze the adoption process of destoners and other improved milling technologies and their effects on the quality of milling service, the business performance, and the survival rate in the market. Because destoners and other improved devices used to be components of mainly large-scale multi-stage milling machines, only 3 out of 82 sample millers in 2011 and 15 out of 103 millers in 2016 were using destoners. But subsequently, small- and medium-scale multi-stage milling machines with destoners became locally available, and 8 and 11 additional millers newly adopted destoners in 2018 and 2019, respectively. By contrast, many millers without adopting improved technologies were forced to shrink their business or exit the market. Using the doubly robust method and the endogenous switching regression to address the endogeneity of destoner adoption, we find that the adoption of improved rice milling

[1] Improved Basmati is cross-breed between Basmati and high-yielding modern varieties and widely grown in India and Pakistan. It is lower quality but higher yielding than original Basmati rice. The only small amount of other rice varieties is produced solely for farmers' domestic consumption.

[2] Improved milling machines have pre-cleaners, destoners, graders, and color sorters in addition to de-huskers and polishers, the standard functions of traditional machines (see Appendix Table).

[3] The Pakistani rice is not Basmati, but some type of long grain nonaromatic rice. According to our informal interviews with local rice traders, some sellers blended Mwea rice with imported rice from Pakistan, and they sold it as "Mwea rice."

technologies is associated with higher milling fees, a greater amount of milled rice, and higher profitability. Moreover, the millers using destoners are more likely to survive in the market. These findings confirm the critical importance of improved rice milling technology in enhancing the quality of African rice.

The rest of this paper is organized as follows. Section 2 explains the data and describes the characteristics of sample rice millers in Mwea. Section 3 postulates the hypotheses and explains the empirical strategy, and Section 4 describes the estimation results. Section 5 concludes the paper.

2. Millers in Mwea

Figure 1 presents changes in rice consumption, production, imports, and paddy price in Kenya from 2010 to 2019. After the 2007-2008 food crisis, the paddy price declined over time, consistent with the decline in the world rice price (Kikuchi *et al*., 2021). While rice consumption and imports almost doubled, rice production was stagnant during this period in Kenya. There was a severe drought in 2016 and 2017 in the horn of Africa region, which may have depressed rice production in the country over this period.

The Mwea Irrigation Scheme produces 80 to 88 % of domestic rice in Kenya (Samejima *et al*., 2020), and we study the rice millers in Mwea to inquire into the development process of the rice milling sector. We find that learning new technologies from overseas played a crucial role in the development of rice milling. In what follows, we would like to discuss the history of the development of the rice milling industry and explain our primary data collection in Mwea.

2.1 Brief history

In the Mwea Irrigation Scheme, the history of modern rice milling dates back to 1967 when a public rice miller, Mwea Rice Mill Ltd. (MRM), which had a monopoly right for rice milling service, began operating four lines of large multi-stage milling machine imported from Germany. In 1999 the rice sector was liberalized, and MRM started competing with other millers for milling service. In early periods, operators of multi-stage milling machines received on-the-job-training at MRM, and some moved to other millers later.

In 2000, Mwea Rice Growers Multipurpose Cooperative Society Ltd. (MRGM) purchased a large Chinese multi-stage milling machine without a destoner because they did not realize its importance as they bought the machine from a broker in Nairobi without visiting China. In 2007, a private miller, Mwega, purchased a second-hand small-sized multi-stage milling machine with destoners. But this installation did not influence other millers, probably because Mwega was a small miller at that time.

A significant event occurred in 2010 when the chairman and two workers of MRGM went to China to learn new milling technologies and purchased a new multi-stage milling machine. Notably, the new machine this time was equipped with a destoner, which improved the quality of milled rice by removing small stones and other impurities. In the following period, some owners of millers who had expertise in rice marketing or accumulated wealth through other business activities also started inquiring into new rice milling technologies by visiting machine suppliers in China. As a result, a little over 10 private millers and MRM installed large multi-stage milling machines in the first half of the 2010s. Aside from visiting China, these owners employed experienced operators, especially from MRM and MRGM.

Because small- or medium-sized multi-stage milling machines were locally introduced from China in the late 2010s and the importance of destoners became widely recognized in the milling cluster, other millers, particularly those highly educated, also adopted destoners. By contrast, the other millers either reduced their business while using traditional types of milling machines without de-stoners (so-called “Jets” and “fridges”) or exited the market.

2.2 Data

We visited the Mwea Irrigation Scheme in 2011, 2017, and 2020 to interview the commercial rice millers. As in other rice millers in SSA, their task is primarily to provide milling service for farmers and traders, rather than purchasing paddy and selling milled rice to the markets. Because December and January are the main season of rice harvesting and milling in Mwea, our survey mainly focused on rice millers' characteristics and performance in January 2011, December 2016, December 2018, and December 2019.

There was no official list of rice millers during our survey in 2011 and 2017, and the coverage of the survey gradually expanded over the rounds as we discovered millers operating in this area. In 2011, we visited the millers in Mwea town (locally known as Wanguru or Ngurubani), stretching over 5 km along the Embu-Nairobi highway, connecting Mwea and Nairobi in about 1.5 hours, and in Kandongu town, which is about 4 km off the Embu-Nairobi highway. In 2017, we maintained this strategy, but we also visited other additional mills deemed commercial on a local rice extension officer's advice. The 2020 survey is the most comprehensive, as we compared our list of rice millers with the list that we obtained from the county government, which had also tried to construct a census of all rice millers in the county.

2.3 Descriptive statistics

Table 1 presents our sample millers' basic characteristics by the destoner adoption status, representing improved rice milling technologies including pre-cleaners and graders (see Appendix Table), as of December 2019. The survey coverage was expanded over time, and 62 and 45 millers were added in the 2017 and the 2019 surveys, respectively. The early adopters are the millers that adopted improved machines by 2016, and three did so in 2011. The adoption rates were 3.7% (or 3/82) and 14.6% (or 15/103) in 2011 and 2016, respectively. The late adopters are the millers that adopted destoners and other improved devices after 2016. Because of their adoption, the adoption rate increased to 26.1% (or 22/84) in 2018 and 34.7% (or 33/95) in 2019. Many millers that did not adopt improved technologies exited the market: Between 2012 and 2016, 40 of 41 exited millers were non-adopters, while 52 of 53 exited millers between 2017 and 2019 did not have destoners and other improved devices.

The average year of the establishment was 2008.9, while the early and the late adopters were established in 2005 and 2011 on average, respectively. The Embu-Nairobi highway was constructed in 2007, and one-third of non-adopters and most adopters of improved machines were located along the highway. The average age of main decision-makers was 50 years old, and they were mostly male. Only 45 % of the non-adopters were high school graduates, whereas almost all the decision-makers of adopters were high school graduates. Many decision-makers of non-adopters were previously farmers, whereas those of adopters have work experience in other businesses or formal jobs.

Table 2 presents the total milling capacity, the value of milling machines, and the number of employees. Almost all the sample rice millers had only one milling machine.[4] In 2011 when only three early adopters used destoners, the average milling capacity was similar among three groups of rice millers.[5] From 2011 to 2016, the average capacity of early adopters increased significantly. In 2019, the non-adopters had a total milling capacity of 816 kg per hour, using the traditional type of milling machine. The early adopters had large-sized multi-stage milling machines, with a total milling capacity of 6196 kg per hour, and the late adopters installed small- or medium-sized multi-stage milling machines, with an average milling capacity of 3479 kg per hour.[6]

We also collected the milling machines' present value, measured by the decision-maker's willingness to pay (WTP) in 2016, 2018, and 2019 (Table 2). The non-adopters'

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4 Only nine millers had two machines, and only one had three machines in 2019.

5 Although we visited MRM and MRGM in 2011, we did not formally interview them because their technologies and business size seemed to be too distinct from other millers. We interviewed them in 2017 and 2019.

6 Appendix Table presents that the areas of workshop, storage, and yard were also largest for the early adopters, which were followed by the late adopters, and the non-adopters had the smallest space. The early adopters attract traders by offering their large storage space free of charge.

WTP of milling machines was 0.19 million Kshs in 2019,[7] whereas the early adopters' WTP and the late adopters' WTP were 13.0 million Kshs and 4.9 million Kshs, respectively. Furthermore, the non-adopters employed only 0.5 worker on average, while the early adopters and the late adopters employed 10 and 4 workers, respectively, in 2019 (Table 2).

Table 3 presents the monthly milling performance of sample millers for January 2011, December 2016, December 2018, and December 2019.[8] The average milling fees, which are expected to reflect the milling quality, of the early adopters and the late adopters were 2.64 Kshs per kg and 2.37 Kshs per kg in 2019, respectively, which were substantially higher than the milling fee of the non-adopters of 1.76 Kshs per kg. Over time, the non-adopters' milling fee increased from 1.89 Kshs per kg in 2011 to 2.03 Kshs per kg in 2016 but declined to 1.81 Kshs per kg in 2018 and 1.76 Kshs per kg in 2019, which is likely to reflect decreased demand for their milling service. The early adopters' milling fee increased more substantially from 2.10 Kshs per kg in 2011 to 2.83 Kshs per kg in 2016, when all of them adopted destoners. Similarly, the late adopters' milling fee increased from 1.61 Kshs per kg in 2016 to 2.29 Kshs per kg in 2018 and 2.37 Kshs per kg in 2019. We do not know why the late adopters' milling fee was as low as 1.61 Kshs per kg in 2016 when it was 2.03 Kshs per kg for the non-adopters. It may well be that their strategy was to attract customers by reducing milling fees in the face of competition with early adopters. As may be expected, in 2019, their average milling fee was slightly lower than that of early adopters.

The non-adopters' amount of rice milled for customers declined from 52 tons in 2011 to 26 tons in 2016 and 22 tons in 2019 (Table 3). By contrast, the early adopters' amount of milled rice increased from 109 tons in 2011 to 270 tons in 2016, when they adopted destoners, and further to 422 tons in 2018 and 883 tons in 2019. The late adopters' amount of milled rice also

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[7] In this paper, all the monetary values are deflated using the GDP deflator, and presented in the real value of 2019. The average exchange rate in December 2019 was 101.5 Kshs to 1 USD.

[8] Appendix Table presents the annual amount of rice sold in 2019. We believe that the monthly data we use are more accurate than the annual data, because the recall period is shorter.

increased substantially from 56 tons in 2016 to 220 tons in 2018 and 255 tons in 2019, as they increased destoner adoption. Figure 2 presents changes in the market share of the amount of milled rice by these three groups. In 2011, the non-adopter group dominated the milling service market with a market share of 80%, whereas the early adopter group rapidly increased its market share to 62% in 2016. The late adopters had their market share at 8% and 5% in 2011 and 2016, respectively, but their market share sharply increased to 27% in 2018 and 26% in 2019. The non-adopters lost a significant market share to the improved technology adopters and had only 7% of the market share in 2019. The near demise of non-adopters strongly indicates that milling machines with improved devices are profitable.

About 40 % of sample rice millers purchased paddy[9] and sold milled rice to consumers, supermarkets, and traders (Table 4). The proportion of millers that sold milled rice was similar across the three groups, and it did not change over time. Although not reported in Table 4, a few millers used brand names when they sold milled rice (e.g., four early adopters and three late adopters in 2019). The non-adopters of destoners selling rice sold 5.2 tons in 2016, 7.0 tons in 2018, and 6.8 tons in 2019, whereas the early adopters selling rice sold 249 tons in 2016, 302 tons in 2018 and 217 tons in 2019. The amount of rice sold by the late adopters increased from 12 tons in 2016 to 54 tons in 2018 and 38 tons in 2019, which remain small compared to their rice milled for customers. These observations suggest that some early adopters shifted their business focus to selling rice, while the late adopters increased their share in the milling service. The non-adopters' price of sold rice declined from 124.4 Kshs per kg in 2016 to 120.5 Kshs per kg in 2018 and 115.4 Kshs per kg in 2019, while the early adopters' price of rice sold decreased from 141.0 Kshs per kg in 2016 to 138.2 Kshs per kg in 2018 and 131.4 Kshs per kg in 2019. The late adopters sold rice at 132.8 Kshs per kg in 2016. The price substantially increased to 140.6

[9] There is no contract farming system for rice, and these millers do not provide farmers with credit.

Kshs per kg in 2018 and 130.4 Kshs per kg in 2019, which became comparable to the early adopters' rice price.[10]

We calculated the monthly capacity utilization rate to examine the milling productivity per machine's capacity operating for 200 hours per month (Table 5).[11] The non-adopters reduced the capacity utilization rate over time from 0.60 in 2011 to 0.30 in 2016, 0.25 in 2018, and 0.21 in 2019, which suggests the decreased demand for the non-adopters' milling service. The early adopters also reduced the capacity utilization rate from 1.33 in 2011 to 0.40 in 2016 when they initially adopted large-scale multi-stage milling machines but could not attract many customers for milling service. However, the early adopters increased the capacity utilization rate to 0.64 in 2018 and 1.36 in 2019 when they substantially increased the milling service, as observed in Table 3. The late adopters initially had a high capacity utilization rate of 1.37 in 2011, which dropped to 0.38 in 2016. Nevertheless, the late adopters maintained the capacity utilization rate at 0.38 in 2018 and slightly increased it to 0.45 in 2019, unlike the declining performance of the non-adopters. This monthly capacity utilization rate reflects the milling performance in the main season. We also calculated the annual capacity utilization rate in 2019 (Appendix Table) and found that the non-adopters had 0.28 and the late adopters had 0.45, comparable to their performance in the main season, whereas the early adopters had only 0.13. This result suggests that the early adopters could not attract many customers and substantially reduced their milling performance in the offseason, leaving their large-scale milling machines idle.

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[10] Paddy quality is also important in determining the overall rice quality, and farm level agronomy affects the quality of paddy, including levelling, fertilizer application, amount of water during crop establishment and pest and disease control. Mechanical harvesting has also helped reduce the losses. Traders determine the quality of paddy through observation and checking for moisture content. Many traders have moisture meters and usually check for the moisture content at the time of purchasing. We do not observe a significant difference in the minimum required moisture content across millers (Appendix Table). They also observe the paddy grain to ensure that the pods are full, which is a sign of good quality paddy. But there is no grading system or pricing differential on paddy quality.

[11] The monthly capacity utilization rate is the total amount of milled rice and sold rice (tons per month) divided by the milling capacity of machines for 200 hours of operation (tons per month).

The profit of the non-adopters was negative, -0.08 million Kshs in 2016, -0.05 million Kshs in 2018, and -0.08 million Kshs in 2019 (Table 5).[12] The early adopters' profit was far the largest but declined from 11.5 million Kshs in 2016 to 10.3 million Kshs in 2018 and 2.84 million Kshs in 2019 (Table 5). By contrast, the late adopters' profit substantially increased from 0.03 million Kshs in 2016 to 1.04 million Kshs in 2018 and 2.64 million Kshs in 2019, as they upgraded the milling machines. Since the absolute amount of profit depends on the amount of investment, we also calculated the ratio of profit to milling capacity per month as an alternative indicator of the milling business's profitability. The non-adopters had -0.04 in 2016, -0.01 in both 2018 and 2019. The early adopters also had negative and declining ratios, -0.001 in 2016, -0.02 in 2018, and -0.20 in 2019,[13] suggesting overcapacity for early adopters, particularly after the late adopters also adopted the improved milling machines. In contrast, although the late adopters initially had a negative ratio of -0.03 in 2016, they increased the profit per capacity to 0.12 in both 2018 and 2019.

3. Hypotheses and Empirical strategy

3.1 Hypotheses

Because, in the early 2010s, the importance of the destoner component was not widely known and the improved technologies were available primarily with the large-sized multi-stage milling machines, which were expensive, the early adopters are expected to be knowledgeable about the

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[12] We calculated profit by subtracting labor cost, purchasing cost of paddy, electricity cost, and maintenance cost and depreciation cost of milling machines from the revenue of milling service and selling rice and bran. The depreciation cost is estimated by assuming the linear depreciation over the usable lifetime, D = (V-S)/(12 x L), where D = monthly depreciation, V = the value of machine, S = the salvage value of the machine after its useful use, assumed to be 10 % of the machine value, L = useful life of the milling machine, assumed to be 10 years (Tokida *et al.*, 2014; Norbu, 2018). The estimation results below are essentially robust to parameter values in reasonable ranges. Because of the data limitation, we did not consider other expenses such as rent of workspace and storage, marketing cost, or tax payment.

[13] The early adopters' average profits are positive because of large positive profits of some millers using large milling machines despite negative profits of other millers. But the average profit-capacity ratios reduce the weight for those large millers and turned out to negative.

urban rice market and to have sufficient wealth to make a large initial investment. By the time when the small- and medium-sized multi-stage milling machines became available in the late 2010s, the importance of special knowledge about the marketing of high-quality rice and wealth would have reduced. Instead, the general human capital represented by education is expected to play a larger role in making proper adoption decisions of milling machines. Moreover, because the millers operating along the highway can attract more large urban traders keen on procuring high-quality milled rice, they have a greater incentive to improve their milling quality. Based on these considerations, we would like to hypothesize that:

> *Hypothesis 1:* "*Those who had acquired knowledge about urban rice market or accumulated wealth through former occupations tended to adopt improved milling technologies early, whereas those highly educated tended to adopt improved technologies later. Moreover, the millers along the highway were more likely to adopt improved technologies.*"

As we have learned in the previous section, because the improved milling technologies were available primarily for large-sized multi-stage milling machines in the early 2010s, these early adopters are expected to provide a higher quality of milling service and market performance in those years. In the late 2010s, small- and medium-sized multi-stage milling machines were introduced in Mwea, which reduced the advantage in high-quality milling service of the early adopters. Moreover, the descriptive analyses above suggest the overcapacity for the early adopters, and, hence, the productivity and profitability of the early adopters' business may have been lower than the late adopters. Based on these observations, we would like to hypothesize that:

Hypothesis 2: "*Both the early and the late adopters improved the milling quality with improved milling technologies, but the late adopters outperformed the early adopters in productivity and profitability because of the excess capacity of the early adopters' milling machines.*"

Furthermore, during the 2010s, millers who adopted improved machines are expected to have improved their milling and overall business performance. In contrast, the other millers kept using traditional milling machines and performed poorly or exited the market because they lost the milling service business to the adopters. Thus, we also would like to test the following hypothesis,

Hypothesis 3: "*The non-adopters tended to exit the market because they lost milling service business to the adopters of improved machines, who were more likely to survive in the business.*"

3.2 Doubly Robust and Endogenous Switching Regression

We consider an estimation strategy to explicitly control the selection on observables and match millers with similar characteristics. The studies on agricultural technologies use such estimation methods, including propensity score matching, inverse probability weighting, and the doubly robust (DR) method, when no plausible instruments are available (Takahashi and Barrett, 2014; Bellemare and Novak, 2016; Kahn, *et al*., 2019; Mano *et al*., 2020). We apply the DR method, or more precisely, inverse-probability weighted regression adjustment, which combines the regression and propensity score weighting. It is more robust than the propensity score matching estimator and the inverse-probability-weighting estimator and can provide a consistent estimator as long as either the propensity score for destoner use or the outcome regression in terms of miller's characteristics is correctly specified (Wooldridge 2007; Wooldridge 2010, Section

21.3.4).[14] More specifically, we first estimate the binary response model of improved technology adoption,

$$D_{it}^{*} = x_{it}'\beta + \epsilon_{it} \text{ with } D_{it} = \begin{cases} 1 & if \;\; D_{it}^{*} > 0 \\ 0 & if \;\; D_{it}^{*} \leq 0 \end{cases} \tag{1}$$

where D_{it}^{*} is the latent variable of improved technology adoption, x_{it} is the vector of miller *i*'s characteristics in a month of main season in year *t* = 2011, 2016, 2018, 2019, β is the parameter to be estimated, ϵ_{it} is the error term, and the probability of improved technology adoption conditional on the miller's characteristics can be expressed as the probit model,

$$P(D_{it} = 1|x_{it}) = \Phi(x_{it}'\beta) \equiv p(x_{it})$$

where $p(x_{it})$ is the propensity score of improved technology adoption. The miller's characteristics are decision-makers' age, the high school dummy that takes 1 if the decision-maker graduated from high school, the former occupation dummies, and the rice miller's establishment year. The year dummies are also used. Using the estimated propensity $\hat{p}(x_{it})$, we estimate the regression parameters γ's by using the following set of the inverse probability weighting linear least squares problems,

$$\min_{\gamma_1} \sum_i \sum_t D_{it}(Y_{it} - x_{it}'\gamma_1)^2 / \hat{p}(x_{it})$$

$$\min_{\gamma_0} \sum_i \sum_t (1 - D_{it})(Y_{it} - x_{it}'\gamma_0)^2 / [1 - \hat{p}(x_{it})]$$

We estimate the average treatment effect on the treated (ATT) of the improved technology adoption on outcome Y as the average of the difference in predicted values of outcomes,

$$\hat{\tau}_{ATT,DR} = \bar{x}_1'(\hat{\gamma}_1 - \hat{\gamma}_0) \tag{2}$$

where $\overline{x_1} = n_1^{-1} \sum_i \sum_t D_i x_{it}$ is the vector of average characteristics of millers (including the constant term) over the improved technology adopters and n_1 is the number of

[14] We used STATA command *teffects ipwra* to implement the DR method.

improved technology adopters. Here, $\hat{\tau}_{ATT,DR}$ is the DR estimator of ATT. The outcome variables are the milling fee, the amount of rice milled for customers, the rice purchasing and selling dummy, which takes 1 if the miller purchased paddy and sold rice and 0 otherwise, the price of sold rice, the amount of sold rice, the capacity utilization rate, the gross profit, the gross profit per capacity, and the survival dummy, which takes 1 if the miller continued operation until the next period of our observation and 0 otherwise.

The other empirical strategy that we use is the endogenous switching regression (ESR), and this method is also often used in the studies of technology adoption in agriculture to address the endogeneity bias due to unobserved characteristics, which is assumed away by the doubly robust method (Di Falco, *et al.*, 2011; Konje *et al.*, 2018; Bairagi, *et al.*, 2020). The first step is to estimate the binary response model of improved technology adoption (1), and the second step specifies the relationship between the outcome variable Y_{it} and a vector of miller's characteristics x_{it} for improved technology adopters and non-adopters, separately,

$$\text{Destoner adopters:} \qquad Y_{1it} = x'_{1it}\delta_1 + \mu_{1it} \text{ if } D_{it} = 1 \qquad (3)$$

$$\text{Nonadopters:} \qquad Y_{0it} = x'_{0it}\delta_0 + \mu_{0it} \text{ if } D_{it} = 0 \qquad (4)$$

where subscripts 1 and 0 represent adopters and non-adopters, respectively, δ's are the vectors of regression coefficients, and μ's are the random error terms. The error terms in equations (1), (3), (4) are assumed to be jointly and normally distributed with mean vector zero and the following covariance matrix:

$$\Omega = cov(\epsilon_{it}, \mu_{1it}, \mu_{0it}) = \begin{bmatrix} \sigma_\epsilon^2 & \sigma_{\epsilon 1} & \sigma_{\epsilon 0} \\ \sigma_{\epsilon 1} & \sigma_1^2 & \cdot \\ \sigma_{\epsilon 0} & \cdot & \sigma_0^2 \end{bmatrix}$$

where $\sigma_\epsilon^2 = var(\epsilon_{it}) = 1$, $\sigma_1^2 = var(\mu_{1it})$, $\sigma_0^2 = var(\mu_{0it})$, $\sigma_{\epsilon 1} = cov(\epsilon_{it}, \mu_{1it})$, $\sigma_{\epsilon 0} = cov(\epsilon_{it}, \mu_{0it})$, and the covariance between μ_{1it} and μ_{0it} are not defined because they are not observed simultaneously (Green, 2012). The conditional expectation of the outcome of the destoner adopters in the actual case of adopting destoners can be expressed as

$$E(Y_{1it}|D_{it} = 1,\ x_{1it}) = x'_{1it}\delta_1 + E(\mu_{1it}|D_{it} = 1, x_{1it}) = x'_{1it}\delta_1 + \sigma_{\epsilon 1}\lambda_{1it} \quad (5)$$

where $E(\mu_{1it}|D_{it}=1,x_{1it})=\sigma_{\epsilon 1}\frac{\phi(x'_{1it}\beta)}{\Phi(x'_{1it}\beta)}\equiv\sigma_{\epsilon 1}\lambda_{1it}$. Analogously, the conditional expectation of the outcome of the destoner adopters in the counterfactual case of not adopting destoners can be expressed as

$$E(Y_{0it}|D_{it}=1,x_{1it})=x'_{1it}\delta_0+E(\mu_{0it}|D_{it}=1,x_{1it})=x'_{1it}\delta_0+\sigma_{\epsilon 0}\lambda_{1it} \quad (6)$$

Following Heckman *et al.* (2001) and Di Falco *et al.*, (2011), we calculate the covariate-specific effect of the treatment on the treated as the difference between equations (5) and (6),

$$E(Y_{1it}|D=1,\ x_{1it})-E(Y_{0it}|D=1,x_{1it})=x'_{1it}(\delta_1-\delta_0)+(\sigma_{\epsilon 1}-\sigma_{\epsilon 0})\lambda_{1it}$$

Taking the average of this value over the destoner adopters, we obtain the ATT estimator of the destoner adoption using the endogenous switching regression,

$$\hat{\tau}_{ATT,ESR}=\bar{x}'_1(\hat{\delta}_1-\hat{\delta}_0)+(\hat{\sigma}_{\epsilon 1}-\hat{\sigma}_{\epsilon 0})\bar{\lambda}_1$$

where $\overline{x_1}=n_1^{-1}\sum_i\sum_t D_i x_{it}$ is the vector of average characteristics of millers (including the constant term) over the destoner adopters, $\bar{\lambda}_1$ is the average inverse mill's ratio calculated using the regression parameter estimated in model (1), δ's and σ's are parameters of regression (5) and (6) to be estimated.[15] Because we do not have a decent instrument for destoner adoption, we rely on the nonlinearity of the inverse mill's ratio for the identification in parameter estimation (Wooldridge, 2010). Analogously, we also estimate the average treatment effect on the untreated (ATUT), the hypothetical effect of adopting improved technologies for non-adopters,

$$\hat{\tau}_{ATUT,ESR}=\bar{x}'_0(\hat{\delta}_1-\hat{\delta}_0)+(\hat{\sigma}_{\epsilon 1}-\hat{\sigma}_{\epsilon 0})\bar{\lambda}_0$$

where $\overline{x_0}=n_0^{-1}\sum_i\sum_t(1-D_i)x_{it}$ is the vector of average characteristics of millers (including the constant term) over the non-adopters, $\bar{\lambda}_0$ is the average inverse mill's ratio for non-adopters. We use ATUT estimates to examine whether non-adopters had lower expected profitability, which may be why they did not adopt improved technologies.

[15] We used STATA command *movestay* to implement the ESR method.

4. Estimation Results

Table 6 presents the estimation results of the probit model of improved technology adoption, represented by destoner adoption, in 2011, 2016, 2018, and 2019, respectively. We combine the early adopters and the late adopters to create a destoner adopter category to enable the analyses with the limited sample size. The estimated effect of the highway dummy was strictly significant, and its magnitude increased gradually over time from 0.16 in 2011 to 0.35 in 2019. In 2016, when the early adopters adopted destoners, the main decision-makers of the destoner adopters were found to have former work experience in rice milling and trading or other business and formal jobs. In 2018 and 2019, the main decision-makers of the destoner adopters were found to have higher education but less previous work experience in the rice market. These results are consistent with Hypothesis 1.

Table 7 presents the estimation results of the DR method and the ESR method, and the ATT estimates of improved technology adoption are similar between the two methods. We also estimated the ATT for early adopters and late adopters separately using the DR method and the ATUT of improved technology adoption using the ESR method. The adoption of improved milling technologies increased the milling fee by 0.77 Kshs per kg or 2.00 Kshs per kg for the adopters in general, 0.84 Kshs per kg for the early adopters, and 0.73 Kshs per kg for the late adopters, while it would have also increased the milling fee of the non-adopters by a smaller magnitude of 0.47 Kshs per kg if they adopted the improved machines. These findings are consistent with the first part of Hypothesis 2. The improved machine adoption also increased the amount of rice milled for customers by 334.9 tons or 357.3 tons for the adopters in general, 431.4 tons for the early adopters, 163.3 tons for the late adopters, while it would have also increased the amount of milled rice for the non-adopters by a greater magnitude of 730.7 tons.

The DR estimates of ATT of improved technology adoption on the probability of selling rice were not statistically significant. Nevertheless, according to the corresponding ESR estimate, the improved technology adoption increased the probability of selling rice by 0.21 for the adopters, whereas it would have reduced the probability of selling rice for the non-adopters. The adoption of improved machines increased the price of sold rice by 10.64 Kshs per kg or 16.92 Kshs per kg for the adopters in general, 4.40 Kshs per kg for the early adopters, which is insignificant, 17.57 Kshs per kg for the late adopters, which is strictly significant, whereas it would have reduced by 26.56 Kshs per kg for the non-adopters. We do not know why the adoption of improved milling machines would decrease the non-adopters' price of sold rice. We suspect that because the decision-makers of the non-adopters lack former work experience in rice marketing or general education, they were incapable of increasing the rice price simply by adopting improved machines. These findings are consistent with the first part of Hypothesis 2. The adoption of improved technologies increased the amount of sold rice by 143.5 tons or 107.4 tons for the adopters in general, 236.6 tons for the early adopters, 36.7 tons for the late adopters, whereas it would have reduced by 8.1 tons for the non-adopters.

The adoption of improved machines increased the capacity utilization rate by 0.36 or 0.07 for the adopters in general, 0.46 for the early adopters, 0.20 for the late adopters, and it would have also increased by 0.72 for the non-adopters. The DR estimates of the effect of improved machine adoption on profit were not statistically significant. However, according to the ESR estimates, the improved technology adoption increased the profit by 6.93 million Kshs for the adopters and would have reduced the profit substantially 55.49 million Kshs for the non-adopters. As was explained earlier, because the decision-makers of the non-adopters lack former work experience in rice marketing or general education, we suspect that they were incapable of increasing the profit simply by adopting improved machines. The estimated effect of improved machine adoption on the early adopters' profit-capacity ratio was insignificant but -0.08, suggesting the early adopters' excess capacity. In contrast, the adoption of improved machines significantly increased the late adopters' profit-capacity ratio by 0.14. According to the ESR estimates, the adoption of improved technologies increased the profit per capacity by 0.17

for the adopters in general, but it would have reduced the profit-capacity ratio by 0.14 for the non-adopters. These findings are consistent with Hypothesis 2.

We also estimated the ATT and ATUT of destoner adoption on the millers' survival rate. The adoption of improved technologies increased the probability of survival until the next period of our observation by 0.34 or 0.40 for the early adopters, and it would have also increased the survival probability substantially for the non-adopters.[16] This result is consistent with Hypothesis 3.

5. Concluding remarks

SSA heavily relies on rice imported from Asia to meet the rapidly increasing rice consumption due to population growth and urbanization, despite the governments' effort to improve food security by increasing rice farming productivity. Consumers, especially in urban markets, generally prefer high-quality imported rice over domestic rice, and the price difference is often substantial. Thus, it is commonly argued that African rice cannot compete with Asian rice. Interestingly, however, this is not the case in the case of Mwea rice, which is higher quality than imported Pakistani rice and, hence, more expensive. This study explored why this happened.

This study found that learning improved milling technologies from abroad triggered the rice milling industry's transformational improvement in the largest rice production area, Mwea, in Kenya. After the 2007-2008 food crisis, a few owners of rice millers with expertise in rice marketing and accumulated wealth through other businesses visited China and learned the importance of destoners and other improved rice milling machines in improving the quality of milled rice. They adopted large-scale multi-stage rice milling machines with destoners and other improved technologies in the first half of the 2010s and successfully enhanced the milling quality of rice and business performance. In the late 2010s, small- and medium-scale multi-stage

[16] Because we observed the late adopters' complete technology adoption only in the 2019 survey, we cannot estimate their effect on survival.

rice milling machines were introduced to Mwea by followers, and improved rice milling technologies were more widely adopted in the cluster, contributing to Mwea rice's competitiveness against imported rice in the market. These findings strongly indicate the critical importance of learning new useful knowledge from abroad for improving the performance of small enterprises in SSA.

These findings may have significant implications for other SSA countries struggling to improve the quality of milled rice. The critical point is that the introduction of small- and medium-scale multi-stage rice milling machines reduced the financial burden on potential adopters and thereby assisted the wide-spread adoption of the new technology. In other words, the choice of appropriate technology is likely to be of crucial importance for SSA because the profitability of investment in improved machines varies and may not always be positive. To the extent that knowledge of various improved milling machines is a local public good, there is room for the government to provide appropriate information about the cost and benefit of various rice milling machines. Furthermore, we must note that although the adoption of improved milling machines significantly improved the quality of rice and the performance of millers in Mwea, paddy produced in Mwea is a high-quality improved Basmati type which is uncommon in SSA. Whether the adoption of milling machines with destoners will enhance the quality of milled rice and millers' performance in areas where more popular rice varieties are grown is a critical issue to be explored in future studies.

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Table 1: Basic characteristics of sample millers in 2019 by destoner adoption[a]

	Total	Nonadopters	Early adopters[b]	Late adopters[c]
No. of millers (% destoner adoption)				
2011	82	72	6	4
	(3.7)	(0)	(50)	(0)
2016	103	82	15	6
	(14.6)	(0)	(100)	(0)
2018	84	57	14	13
	(26.1)	(0)	(100)	(61.5)
2019	95	62	14	19
	(34.7)	(0)	(100)	(100)
Exit				
2012-2016	41	40	1	0
2017-2019	53	52	1	0
Establishment year	2008.9	2008.9	2005.4	2011.4
	(8.8)	(6.3)	(12.6)	(11.6)
On the highway (=1)	0.52	0.33	0.92	0.84
Characteristics of decision-maker				
Age	49.8	50.4	49.7	47.8
	(10.4)	(10.9)	(10.8)	(8.6)
Female (=1)	0.31	0.33	0.21	0.31
High school/above (=1)	0.61	0.45	1	0.84
Former occupation				
Farmer (=1)	0.38	0.43	0.21	0.32
Rice milling & trading (=1)	0.17	0.22	0.14	0.05
Business & formal jobs (=1)	0.35	0.22	0.64	0.58
Mechanic (=1)	0.10	0.13	0	0.05

a. Standard deviations of continuous variables are in parentheses. The survey coverage was expanded over time, and 62 and 45 millers were added in the 2016 and the 2019 surveys, respectively.
b. The early adopters are the millers that adopted destoners by 2016, and three of them did so in 2011.
c. The late adopters are the millers that adopted destoners only after the 2016 survey, and eight of them did so in 2018.

Table 2: Total milling capacity, WTP of milling machines, the number of employees of millers by destoner adoption

	Total	Nonadopter	Early adopter	Late adopter
Capacity (kg/hour)				
2011	468.8	472.6	445.0	435.0
	(227.9)	(237.5)	(89.1)	(225.7)
2016	1139.0	538.0	4453.3	966.6
	(3032.2)	(385.3)	(7175.7)	(581.9)
2018	2088.8	819.8	6196.4	2838.4
	(4377.6)	(575.2)	(8328.0)	(4710.2)
2019	2076.7	815.9	6196.4	3478.9
	(4298.7)	(574.3)	(8327.9)	(5113.0)
WTP (million Kshs)				
2016	2.15	0.27	13.0	0.44
	(6.44)	(0.15)	(12.3)	(0.27)
2018	3.19	0.19	13.5	4.4
	(8.11)	(0.09)	(14.1)	(7.1)
2019	3.02	0.19	13.0	4.9
	(7.34)	(0.10)	(13.5)	(6.2)
Employees				
2011	1.5	1.4	3.0	1.0
	(1.4)	(1.1)	(3.3)	(0)
2016	1.6	0.90	5.4	1.3
	(2.9)	(0.63)	(6.1)	(0.5)
2018	2.6	0.61	10.4	3.1
	(10.3)	(1.19)	(25.3)	(5.3)
2019	2.6	0.54	10.0	3.8
	(10.4)	(0.73)	(25.3)	(5.7)

Notes: Standard deviations are in parentheses. The total capacity of and the willingness-to-pay for all the milling machines at millers are reported.

Table 3: Monthly performance of milling service by destoner adoption

	Total	Nonadopter	Early adopter	Late adopter
Milling fee (Kshs/kg)				
2011	1.90	1.89	2.10	1.87
	(0.28)	(0.27)	(0.42)	(0.19)
2016	2.12	2.03	2.83	1.61
	(1.18)	(1.27)	(0.54)	(0.42)
2018	2.06	1.81	2.78	2.29
	(0.62)	(0.52)	(0.26)	(0.59)
2019	2.01	1.76	2.64	2.37
	(0.57)	(0.46)	(0.39)	(0.42)
Rice milled for customers (tons)				
2011	58.6	51.8	108.7	99.7
	(50.2)	(48.9)	(30.7)	(39.4)
2016	65.4	26.3	270.3	55.6
	(163.3)	(38.8)	(351.0)	(11.6)
2018	130.0	32.3	422.3	220.3
	(293.5)	(65.5)	(539.7)	(287.7)
2019	198.4	21.6	882.9	255.1
	(791.2)	(38.3)	(1839.9)	(507.2)

Note: Standard deviations are in parentheses. The milling fee is deflated with the GDP deflator (the 2019 value).

Table 4: Monthly performance of rice sales by destoner adoption

	Total	Nonadopter	Early adopter	Late adopter
Proportion of millers which sell milled rice				
2016	0.38	0.37	0.40	0.50
2018	0.41	0.44	0.36	0.37
2019	0.42	0.41	0.35	0.47
Sold rice (tons)				
2016	16.4	5.2	248.6	12.1
	(142.7)	(6.6)	(588.5)	(9.5)
2018	21.9	7.0	301.8	54.1
	(126.5)	(7.6)	(515.6)	(35.9)
2019	16.8	6.8	216.8	38.0
	(83.8)	(8.8)	(323.2)	(49.4)
Price of sold rice (Kshs/kg)				
2016	127.5	124.4	141.0	132.8
	(22.9)	(24.7)	(6.9)	(14.0)
2018	126.4	120.5	138.2	140.6
	(16.3)	(10.5)	(17.7)	(22.2)
2019	120.8	115.4	131.4	130.4
	(15.4)	(9.1)	(18.3)	(5.1)

Note: Standard deviations are in parentheses. The rice price is deflated with the GDP deflator (the 2019 value).

Table 5: Monthly capacity utilization rate, gross profit, gross profit per capacity by destoner adoption

	Total	Nonadopter	Early adopter	Late adopter
Capacity utilization rate				
2011	0.70	0.60	1.33	1.37
	(0.57)	(0.50)	(0.67)	(0.65)
2016	0.32	0.30	0.40	0.38
	(0.35)	(0.37)	(0.26)	(0.14)
2018	0.34	0.25	0.64	0.38
	(0.45)	(0.33)	(0.73)	(0.35)
2019	0.52	0.21	1.36	0.45
	(1.65)	(1.36)	(3.03)	(0.58)
Profit (million Kshs)				
2016	1.71	-0.08	11.5	0.03
	(18.9)	(0.49)	(48.3)	(0.87)
2018	1.99	-0.05	10.3	1.04
	(18.1)	(0.23)	(42.7)	(2.90)
2019	0.92	-0.06	2.84	2.64
	(11.3)	(0.20)	(27.6)	(9.0)
Profit per Capacity (million Kshs/kg)				
2016	-0.03	-0.04	0.001	-0.03
	(0.22)	(0.20)	(0.35)	(0.17)
2018	0.01	-0.01	-0.02	0.12
	(0.20)	(0.08)	(0.34)	(0.31)
2019	-0.01	-0.01	-0.20	0.12
	(0.36)	(0.09)	(0.75)	(0.45)

Note: Standard deviations are in parentheses. The profit is deflated with the GDP deflator (the 2019 value). Capacity utilization rate is the ratio between the total amount of milled rice and sold rice (tons per month) to the milling capacity of 200 hours of operation (tons per month). Profit per capacity is the ratio between the profit (million Kshs per month) to the milling capacity of 200 hours of operation (kg per month).

Table 6: Determinants of Improved Technology Adoption (Probit)

	2011	2016	2018	2019
Age	0.005***	0.001	-0.004	-0.003
	(0.002)	(0.003)	(0.004)	(0.003)
High school	-0.03	0.005	0.21**	0.22***
	(0.03)	(0.06)	(0.10)	(0.08)
Rice miller & trading	0.13	0.23***	-0.11	-0.18*
	(0.09)	(0.09)	(0.11)	(0.09)
Business & formal jobs	---	0.23***	0.09	0.06
		(0.06)	(0.10)	(0.09)
Mechanic	---	0.21**	-1.10**	-0.28**
		(0.10)	(0.15)	(0.12)
Other occupation	-0.12***	---	---	---
	(0.03)			
Year of establishment	-0.0006	-0.001	0.00003	0.003
	(0.002)	(0.003)	(0.004)	(0.003)
Highway	0.16**	0.23***	0.24***	0.35***
	(0.06)	(0.07)	(0.07)	(0.04)
Log pseudo-likelihood	-4.267	-29.63	-31.86	-33.90
Obs.	81	103	82	93

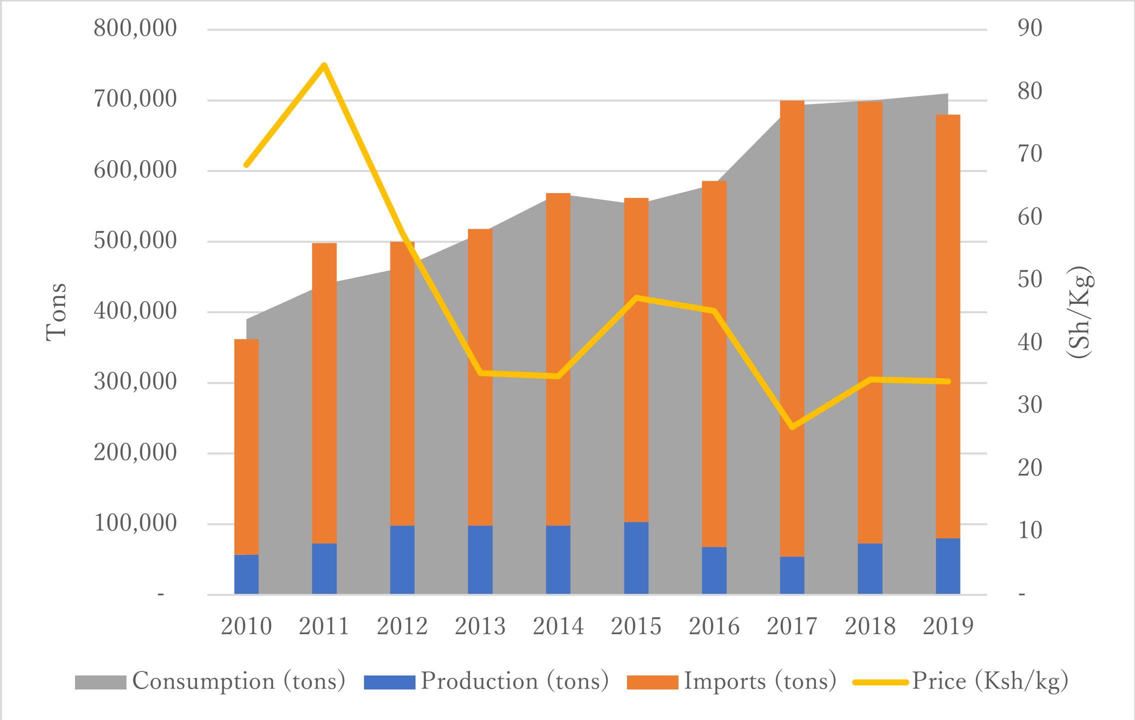
Notes: The marginal effects are reported. The numbers in parentheses are robust standard errors. ***, **, * indicate statistical significance at the 1, 5, 10% levels, respectively.

Table 7: Effects of Improved Milling Technologies (Doubly Robust & Endogenous Switching Regression)

	Milling Fee (Kshs/kg)	Rice milled (ton)	Sell milled rice (=1)	Price of rice (Kshs/kg)	Rice sold (ton)	Capacity util. rate	Profit (mill. Kshs)	Profit per Capacity (million Kshs/kg)	Survival (=1)
Doubly Robust									
ATT	0.77***	334.9***	-0.04	10.64**	143.5**	0.36**	5.93	0.01	0.34***
	(0.09)	(147.7)	(0.10)	(4.34)	(62.4)	(0.17)	(3.76)	(0.06)	(0.12)
Early adopter's ATT	0.84***	431.4***	-0.12	4.40	236.6**	0.46*	8.03	-0.08	---
	(0.12)	(160.4)	(0.11)	(5.95)	(111.4)	(0.26)	(5.92)	(0.08)	
Late adopter's ATT	0.73***	163.3*	-0.04	17.57***	36.7***	0.20**	2.20	0.14*	---
	(0.12)	(98.1)	(0.10)	(5.23)	(9.9)	(0.12)	(1.46)	(0.07)	
Endogenous Switching									
ATT	2.00***	357.3***	0.21***	16.92***	107.4***	0.07*	6.93***	0.22***	0.40***
	(0.03)	(34.5)	(0.02)	(1.18)	(18.9)	(0.04)	(2.33)	(0.01)	(0.03)
ATUT	0.47***	730.7***	-1.41***	-26.56***	-8.1***	0.72***	-55.49***	-0.10***	1.32***
	(0.02)	(9.47)	(0.02)	(0.38)	(4.4)	(0.02)	(1.04)	(0.004)	(0.02)

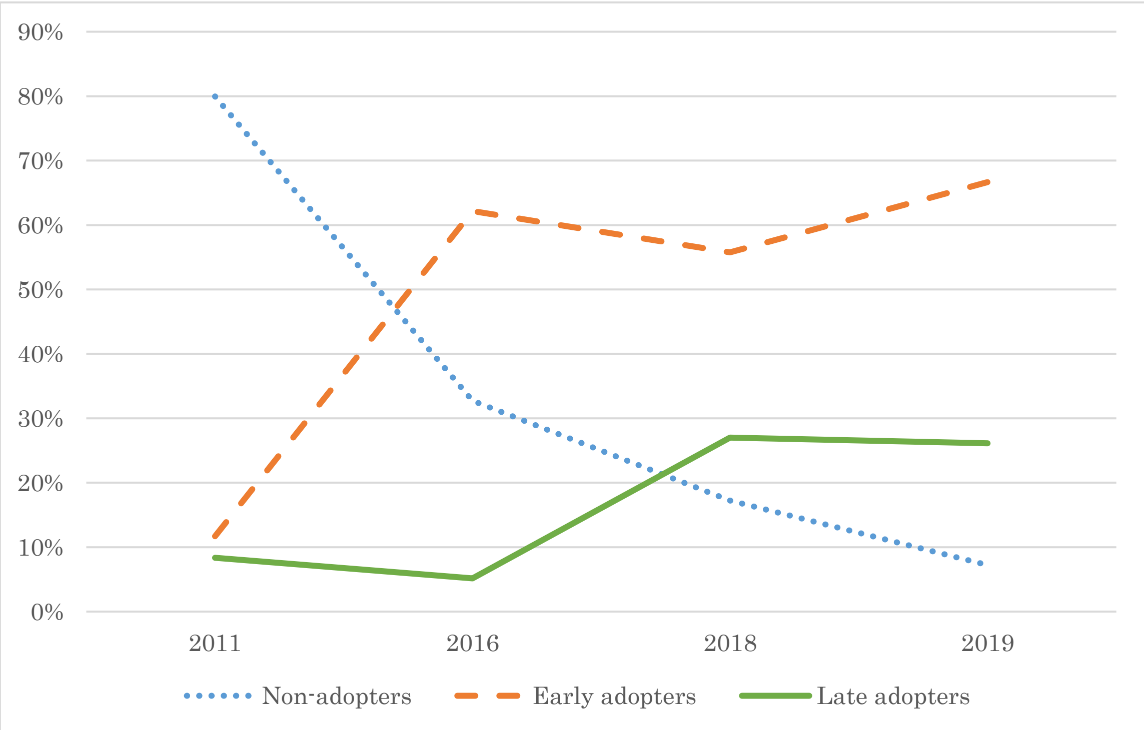
Notes: Robust standard errors are in parentheses. ***, **, * indicate statistical significance at the 1, 5, 10% levels, respectively. The miller's characteristics are also controlled in the analyses: the age of decision-makers; the high school dummy, which takes 1 if the decision-maker graduated from high school; the former occupation dummies; the establishment year of the rice miller; and the year dummies.

Figure 1: Rice consumption, production, imports, and paddy price in Kenya



Source: Kenya National Bureau Statistics 2020.

Figure 2: Market Share of Rice Milled for Customers by Destoner Adoption



Note: The early adopters are the millers that adopted destoners by 2016, and three of them did so in 2011. The late adopters are the millers that adopted destoners only after the 2016 survey.

Appendix Table: Other characteristics of millers in 2019 by destoner adoption

	Nonadopter	Early adopter	Late adopter
Functions of milling machines (=1)			
Pre-cleaner	0	0.93	1
De-husker	1	1	1
Polisher	0.98	1	1
Grader	0.03	0.93	0.68
Color sorter	0	0.57	0.11
Area of workshop & storage (m^2)	262.5	2595.2	949.4
	(336.0)	(2470.3)	(898.6)
Area of yard (m^2)	23.9	3801.5	553.6
	(69.9)	(6076.3)	(1813.6)
Milled rice to paddy ratio (%)	62.0	65.7	64.1
	(3.56)	(3.8)	(2.7)
The minimum moisture content (%)	12.6	12.0	12.9
	(1.1)	(1.2)	(0.8)
Price of bran sold (Kshs/kg)	5.7	12.9	12.0
	(3.1)	(2.7)	(3.3)
The annual amount of bran sold (tons)	37.1	196.9	280.2
	(253.5)	(521.9)	(1097.2)
The annual amount of rice milled (tons)	136.2	3766.6	12353.2
	(203.3)	(5222.8)	(46901.1)
The annual amount of rice sold (tons)	37.7	3355.4	156.2
	(74.7)	(7072.9)	(214.3)
Capacity utilization rate (annual)	0.28	0.13	0.45
	(0.28)	(0.23)	(0.50)

Notes: Standard deviations of continuous variables are in parentheses. The total capacity of and the willingness-to-pay for all the milling machines at millers are reported.

Abstract (in Japanese)

要約

サハラ以南のアフリカ(SSA)の国々は、アジアからの輸入米に大きく依存している。これは、コメの需要が急速に増加し、また消費者がアジアの高品質のコメを好むためである。ケニアでは2010年頃にいくつかの起業家精神に富む精米業者らが中国から新しい精米技術を学び、石抜き装置付きの、改良された大型精米機を採用するようになった。その後、小型の改良精米機が導入され、より広く採用された。改良精米機を採用したこれらの精米業者は、輸入米と競争できる高い品質の精米と業績の改善に成功した。一方、改良精米機を採用しない他の多くの精米業者は、事業を縮小するか、業界からの撤退を余儀なくされた。

キーワード: コメの品質、精米、石抜き機、ケニア、サハラ以南のアフリカ

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