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Gendered implications of the waves of COVID-19 and economic upgrading trajectories in digital value chains

Insights from Kenyan agricultural platforms

Aarti Krishnan,[1] Monica Nganga,[2] Tim Foster[1]

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Abstract: Women play a critical yet under-researched role in global digital agri-food value chains, especially in smallholder production, which affects how they are able to economically upgrade (improve crop yields and product quality, and increase product diversification). Research suggests that women's participation in agricultural platform-driven value chains facilitates the overcoming of barriers such as access to productive resources and engenders upgrading. However, studies have shown mixed evidence of the benefits of ag-platforms, and there are very limited data on female farmers' contribution. Their economic upgrading possibilities are further compounded by the onset of shocks such as COVID-19. Predominantly only anecdotal evidence exists of how such shocks impact women in agriculture generally, let alone those using digital platforms. This paper seeks to answer the question: To what extent has the intensity of COVID-19 affected economic upgrading possibilities for women in platform-driven ag-value chains? The paper attempts to unpack economic upgrading through the different regimes of COVID-19, illustrating the dynamic effects experienced by women living through the shock. The paper uses a mixed methods approach, combining daily transaction data for over 3,000 farmers from 2019 to 2021 with 40 interviews of various value chain actors. The results show that women have been able to upgrade through the shock in terms of crop productivity and product quality more successfully than men, although there are differences across the different regimes of COVID-19; however, women have downgraded in terms of product diversification. The results are robust using pooled OLS, fixed effects, random effects, and seemingly unrelated regressions. The paper highlights a critical need to unpack shocks as a succession of regimes, rather than treating them as homogeneous entities, in order to provide a more holistic understanding of how women cope.

Key words: digital, platforms, agriculture, gender, upgrading, value chains

JEL classification: O13, O19, D80

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[1] University of Manchester, UK, corresponding author: aarti.krishnan-2@manchester.ac.uk; [2] University of Nairobi, Kenya

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

Digital agricultural platforms (otherwise known as digital transaction platforms, which are third-party applications or apps used to facilitate transactions between two or more user groups (Koskinen et al. 2018), are often touted as a means to promote economic upgrading opportunities in agricultural value chains (AVCs) in middle- and low-income countries (e.g. Tsan et al. 2019). However, significant research has shown that, despite using digital platforms, women continue to face disproportionate barriers to participation in agro-value chains (Quisumbing et al. 2014).

The COVID-19 pandemic seems to have further restricted opportunities for women to economically upgrade in digital AVCs. For instance, significant research has alluded to economic downgrading (in terms of lower income and marginalization from participation) occurring in India and Nepal and especially for female farmers who are digitally illiterate (e.g. Adhikari et al. 2021; Alvi et al. 2021). However, most of these studies are anecdotal and often assume COVID-19 to be a homogeneous shock, rather than unpacking the dynamic implications on women through the shock. With this in mind, this paper attempts to answer the question: To what extent has the intensity of COVID-19 affected economic upgrading possibilities for women in platform-driven AVCs?

The paper makes an important contribution to the value chain literature by focusing on how new digital intermediaries in value chains affect upgrading opportunities during shocks. This represents a move away from the dominant GVC literature on lead firms and how they govern the chain and affect upgrading opportunities for other actors such as farmers. Furthermore, given that much of the empirical work in this space is anecdotal, with a minimal focus on gender, this is one of the first studies that explicitly attempts to use detailed transaction-level data along with interviews to ascertain the specific ways in which female farmers upgraded through the pandemic.

The rest of the paper is structured as follows: Section 2 outlines the key literature related to ag-platforms, gender, and economic upgrading in value chains. Section 3 covers the case context of Kenya and the data collection and methodologies employed. Section 4 reports the econometric results (a) considering COVID-19 as a homogeneous shock, (b) across the regimes of COVID-19, (c) using an alternative measure for county-level stringency, and unpacks the implications for female farmers. Section 5 concludes the paper, with thoughts on future directions for research.

2 Ag-platforms, gender, and economic upgrading

Ag-platforms offer the bundling of multiple services from production—such as market information (price, weather) and extension services (good agricultural practices, pest and disease control) and machinery leasing—to downstream services connecting farmers to buyers (processors, wholesalers, retailers) along with a host of complementary services such as logistical services, working capital loans, insurance, and financial transactions through digital wallets (Aker et al. 2016; Krishnan et al. 2020; Tsan et al. 2019). All these services are disparately accessible in traditional agricultural value chains (those that are not intermediated by digital platforms). Ag-platforms or apps, which have proliferated in Africa, are most commonly used through feature phones, where the use of text messages and Unstructured Supplementary Service Data (USSD)[1] is common; and more recently through more sophisticated apps via smart phones (Aker et al. 2016).[2]

Much research has suggested that ag-platforms offer farmers significant potential to economically upgrade (Tsan et al. 2019). In a digital value chain context, economic upgrading has been defined as the 'ability of a firm or an economy to use digital products that enable a move to more profitable and/or technologically sophisticated capital and skill intensive niches' (Barrientos et al. 2011; Gereffi 1999). Humphrey and Schmitz (2002) identify various forms of economic upgrading: (i) the introduction of new and/or more sophisticated products (product upgrading); (ii) the implementation of new methods to transform inputs through superior technology and/or industrial organization (process upgrading); (iii) the move into new production tasks in the same industry (functional upgrading); and (iv) moving into a new industry altogether (chain upgrading). Much of the focus within agriculture has been on product and process upgrading, which includes increasing crop productivity in terms of yields, product sophistication in relation to better quality, and product diversification, which involves expanding the basket of products (Barrientos et al. 2011; Oduol et al. 2017; Ponte 2020; Rao and Qaim 2011). Economic downgrading, the opposite of upgrading, can also occur when there is a fall in yields, lower quality, or a reduction in product concentration (Pasquali et al. 2021).

In terms of product and process upgrading of crop yields, Kilimo Salama, a weather-based mobile app in Kenya, provides insurance for farmers' inputs (e.g., seeds, fertilizers, chemicals) and sends text messages suggesting ways to improve farming techniques. Kilimo Salama reported a 50 per cent increase in crop yields as a result of insurance for farm inputs in 2018, with steeper increases for women than men. Krone et al. (2016) found that in Kenyan horticulture ICT led to positive economic upgrading in terms of increasing access to knowledge, as well as expanding markets to new buyers. Focusing on smallholder sugar-cane farmers, PAD (2022) found that sending SMS messages with agricultural advice to farmers increased their yields by 11.5 per cent, although these increases applied predominantly to male farmers. Another example, Farmerline—a project that delivers agricultural information via voice messages directly to the mobile phones of female agricultural workers in Cameroon, Ghana, Nigeria, and Sierra Leone—reported increases of up to 55 per cent in farmers' yields. In the same vein, Cavatassi et al. (2009) showed that potato farmers on ag-platforms in Ecuador had an average yield of 8.4 M/T per hectare as compared with 6.4 M/T per hectare for those not on platforms. However, downgrading is also said to occur. For instance, Fafchamps and Minten (2012) find no statistically significant effects of SMS-based platforms in India on the productivity of farmers.

In relation to economic upgrading of product quality, studies have highlighted how critical women are to sustaining the quality of produce and how women are often able to 'adopt' new technologies and 'absorb' training better than men (e.g. Barrientos 2019; Odoul et al. 2017). For instance, the use of the Fairtrade farming apps has enabled women farmers to re-invest social premiums to improve cocoa product quality in Ghana (Fairtrade 2020). With regard to cocoa production in Ghana and India, Barrientos (2014) has shown that women take extra care in post-harvest processes (fermenting and drying), which is time consuming but increases crop quality. Similarly,

[1] Communications protocol used in GSM networks for sending short text messages.

[2] Most ag-platforms operate regionally (where trade occurs within a single world region) or domestically (within the bounds of a particular country or territory), rather than through global value chains. This is because the codification of international standards and rules required for sales to the global North are more complex to operationalize than those regionally (e.g. within the East African Community) or domestically (e.g. within Kenya) (Krishnan et al. 2020).

Odoul et al. (2017) find that female-headed households in Kenya produce better quality avocados than male-headed households.

There are varied studies discussing upgrading/downgrading in relation to product diversification. Broadly, an increase in 'related product diversification' across products within the same sector (such as agriculture) has been associated with increased competitive advantage (Brancati et al. 2017). Specifically, Cole and Fernando (2012) showed that farmers in Gujarat, India, who used ag-platforms diversified beyond cotton by increasing their cumin acreage to balance out lean seasons. Similarly, Banga et al. (2020) and Ginige et al. (2016) found that farmers in Sri Lanka and Uganda using digital technology diversified more than farmers who did not, although they were unable to find any specific gender effects.

Indeed, studies in relation to product diversification for women on ag-platforms are sparse. For instance, Aker and Ksoll (2016) found that the use of mobile phone technology led to increasing product diversity for female farmers in Niger, while Mugabi (2015) and Bello-Bravo et al. (2022) find that women farmers tend to cultivate crops that are less profitable, such as beans or cassava, because they contribute to household food security, while men cultivate more profitable cash crops such as coffee. Female farmers focus on fewer, more profitable crops more frequently than their male counterparts (Barrientos 2014).

The studies referred to above highlight the lack of papers focusing on gendered differences, or discussing implications for female farmers in relation to the economic upgrading potential of participating in ag-platform-driven value chains. Several studies have suggested anecdotally that using ag-platforms is a way of mitigating the discrimination faced by women in traditional GVCs (e.g. UNWomen 2022) by reducing barriers to accessing and using services such as digital skills and finance/credit, and reducing information asymmetries and training gaps, thereby supporting the creation of a level playing field for women (Barrientos 2019). However, the implications for women tend to comprise a mix of downgrading and upgrading prospects. For instance, in relation to product and process upgrading in terms of yields, women farmers tend have a lower intensity of usage of ag-platforms than men across developing countries, which reduces the scope for increasing crop yields (Park 2009).

2.1 Governance in ag-platform-driven value chains

Part of the reason for these differences in economic upgrading potential is attributable to the governance structures emanating from the platform itself (Foster et al. 2018; Sturgeon 2021). In traditional value chains, the governance of agricultural products is often 'buyer-driven', with retailers as lead firms, determining the rules of participation. However, ag-platforms in a value chain context bring about disintermediation by reducing or removing the brokers and middle-men prevalent in traditional value chains, but in doing so themselves act as 'new intermediaries' (Heeks et al. 2014) by setting terms of digital services accessibility and mediating matching between buyers and sellers (Kenney et al. 2020).

In a platform context, governance has been measured in different ways. For instance, Golini et al. (2018) argue that platform governance in a value chain context is relational, in terms of the frequency of interactions with actors that enable the transfer of codified knowledge. Similarly, Pasquali et al. (2021) explain value chain platform governance in relation to transaction stability, suggesting that an increased number of transactions demonstrates loyalty and trust in the relationship. Overarchingly, these studies find that, in the case of the agriculture and light manufacturing sectors, higher transaction stability and increased frequency of interaction lead to economic upgrading. However, it is critical to mention the dearth of studies focusing specifically on the gendered upgrading implications of platform governance. A study conducted in 2018 by the FCDO on women's work opportunities has shown that the Kenyan ag-platform for growing high-value fruit and veg has a policy of non-discrimination, allowing equal opportunity for male and female farmers to seek advice from platform champions or experts, with the aim of creating an inviting and safe space for airing platform-related grievances and questions. The study found that this was cited as an important factor enabling women to increase product quality, although there were insignificant gains in crop yields or product diversification for women (Barrientos and Pallangyo 2018).

2.2 Ag-platform-driven economic upgrading during exogenous shocks

Literature on risk management in supply chains finds that upgrading is said to occur when a firm (or group of actors) is able to continue normal operations or maintain operations during a crisis (e.g. Brandon-Jones et al. 2014; Martin 2012). Similarly, within the trade and value chain literature, actors' adaptive capability when participating in a chain—their ability to prepare for uncertainty and respond to unexpected events, while maintaining continuity of operations—is understood as their ability to continue to upgrade (Gölgeci and Kuivalainen 2020; Miroudot 2020). Furthermore, it is difficult to ascertain a time when the COVID-19 crisis ended. Therefore, we assess the implications during the periods March 2019–February 2020 (pre-COVID) and March 2020–August 2021 (through COVID) for this study.

It is important to note that most studies focusing on shocks such as COVID-19 deem them to be 'homogeneous' in the sense that the effects of the shock are seen as occurring in a static way over the period of the shock. For instance, in relation to upgrading, after the earthquake in Japan in 2011, manufacturers in the motor vehicles industry were observed to diversify in terms of products and suppliers (Matous and Todo 2017). Other studies (e.g. Todo et al. 2015) have shown similar results for complex value chains at the time of the Japanese Tsunami in 2011. Kumar et al. (2021) found that during COVID-19, in Haryana (India), fruit and vegetable farmers were encouraged to join farmer producer companies (FPCs) and use digital services such as digital marketing and credit, enabling them to maintain product yield. Thus, farmers were able to economically upgrade. Similarly, through COVID-19, dairy farmers were organized into local milk grids, and through ag-platforms connected to buyers, which allowed them to maintain high quality through the crisis (Kumar et al. 2021).

These studies fail to account, however, for the heterogeneous intensities that occur through a shock. For example, the intensity of a shock may be greater in the early part of the shock, where there are more unknowns, than after a few months, when governments and other institutions are better able to respond or adapt to the shock. Only a few studies have attempted to unpack the intensity of shocks through interviews and surveys. For instance, Benedek et al. (2021) conducted a survey of 421 farmers in Estonia, Hungary, Portugal, and Romania and found that during COVID-19, farmers were able to increase product diversification by using digital channels, but only at the start of the pandemic (April 2020); by July 2020, the upgrading gains had tapered off.

Exogenous shocks such as COVID-19 and their effect on the gendered economic upgrading possibilities in ag-platform-driven value chains have been insufficiently researched (Tsan et al. 2019). For example, Adhikari et al. (2020) showed that, during COVID-19, lack of digital literacy (lower use of digital products on platforms) reduced women's ability to produce high-quality products and gain better incomes in Nepal. A study by Alvi et al. (2021) found that, because female farmers in Gujarat used digital agro-advisory services and digital payment services through COVID-19, they had higher yields than men (although only 3 per cent of the women used digital products frequently). According to Nchanji et al. (2021), the COVID-19 pandemic impacted both men and women bean producers on ag-platforms in DRC, Ethiopia, and Kenya equally, by curbing access to critical input services such as seeds and chemicals, causing downgrading in terms of falling yields and product quality.

No study to our knowledge has attempted to unpack the gendered implications on upgrading of the various intensities of the COVID-19 shock in digital agro-value chains. We unpack the dynamic nature of the COVID-19 pandemic on upgrading (yields, product diversification, and product quality) for women.

3 Case context, research design, and methods

Women play a critical role in Kenyan agriculture, with smallholder women farmers growing over 70 per cent of Kenya's food (Abass 2018) and over 60 per cent being employed directly or indirectly in agriculture (World Bank nd). Furthermore, Kenya is one of the most advanced countries in East Africa in terms of its ability to adopt digital technologies, due to relatively high levels of ICT infrastructure and payment solutions (Krishnan et al. 2020; Tsan et al. 2019).

3.1 COVID-19 regimes

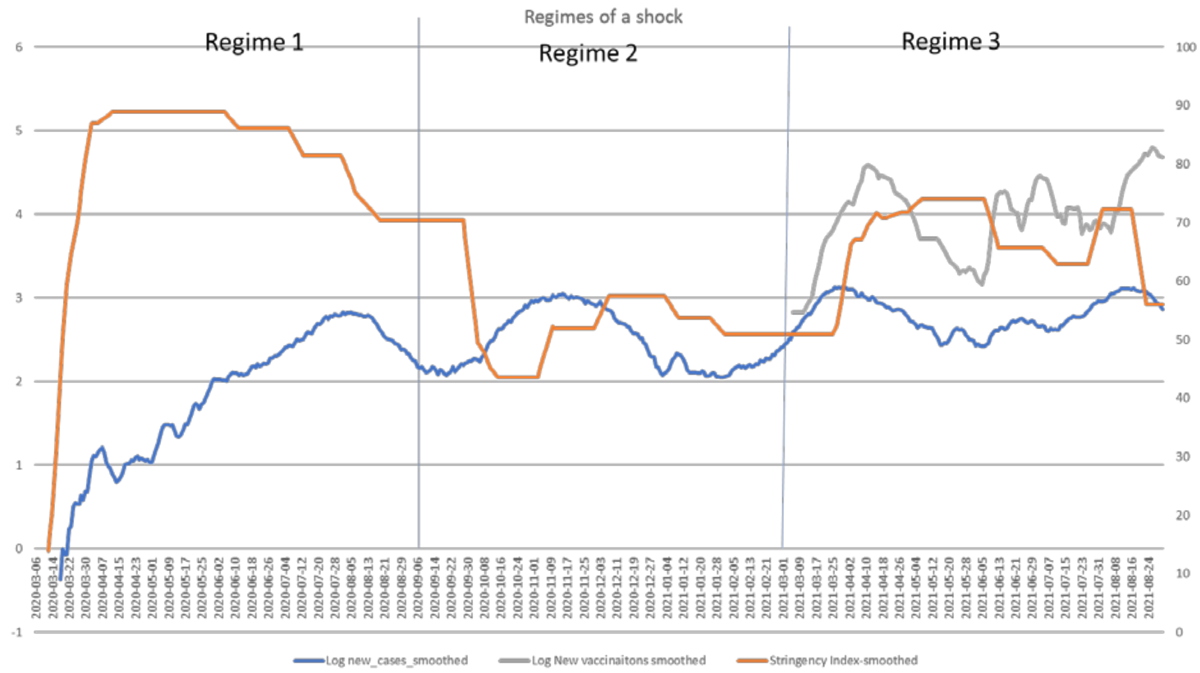
In Kenya, the COVID-19 shock can be divided into three regimes (the pre-COVID situation is regarded as regime 0 in this study), as shown in Figure 1. The first is between March and September 2020. COVID-19 was declared an emergency in March 2020, with stringent measures put in place such as a ban on international flights, school closures, a 'work from home' directive (except for essential workers), a ban on large congregations, and a reduction in the costs of mobile banking and M-money transfers. The government attempted to support the public and businesses through cheaper mobile money transfers and tax breaks (in VAT). These measures continued through August/September 2020. Thus, it was a period of high uncertainty and strict government measures, as can be seen from the exponential increase in the 'stringency index' in Figure 1.

Next came a period of slight relaxation, starting in October 2020, when marketplaces, shops, and restaurants were allowed to open, flights started operating again, freight services recommenced, and schools and other educational institutions re-opened. However, by mid-January 2021, a new variant of COVID-19 was becoming increasingly widespread, which prompted governments to return to more stringent government measures, even though new cases were plateauing. The period between October 2020 and February 2021, an uncertain time when cases and stringency were somewhat stabilized, vaccinations were prevalent, and there was hope of improvement, is referred to as Regime 2 in this study.

Finally, in the period between March 2021 and August 2021 (Regime 3), due to the diffusion of vaccinations, cases were less severe and therefore there was less uncertainty in terms of the effects of the pandemic. Basic curfew measures persisted but only at specific times, and businesses could return to some level of normality.

To enhance understanding of the effects at sub-national level, besides looking at overarching regimes, this study calculated county-level stringency measures using indicators from the Oxford COVID-19 Government Response Tracker (OxCGRT), which collects systematic information of various policy measures taken by governments. This enabled further understanding the 'intensity' of COVID-19 across time within Kenya (for a detailed explanation see Section 3.3).

Figure 1: Regimes of COVID-19



Note: Regime 1: March 2020–September 2020; Regime 2: October 2020–February 2021; Regime 3: March 2021–August 2021.

Source: data complied and calculated by authors using Our World in Data.

3.2 Research design: data collection

Data were compiled by cumulating online reporting by farmers and information collected by ag-platform staff between March 2019 and August 2021. The Kenyan ag-platform is run by one of the largest farmer cooperatives in Kenya (the name of the mobile platform is anonymized for data privacy and security reasons) and offers SMS, IVR (Interactive Voice Response), and USSD options to cereal (e.g. maize, rice), bean (green grams, pigeon peas, black peas), and soybean farmers. The ag-platform provides farmers with access to real-time market and production information (weather, prices), e-extension service support (by codifying agricultural best practices), credit and insurance options, input services (e.g. agro-chemicals), leasing services (e.g. agricultural machinery), and 'guarantee' services (buying produce from farmers and selling it to buyers at a small mark-up).

The app started functioning in early 2018 and currently functions in 24 counties, most registered farmers being in Meru and Trans-Nzoia. It currently has 650,000 registered farmers, but during the study period only 13,176 farmers actively participated on the app, of whom 8,660 were male and 4,516 women. The app collects data in three phases. The first phase is when farmers register on the platform—with the help of village champions and agents (who are hired by the ag-platform)—and must provide their banking and social security details and information on demography and history of production. The second phase includes data collection on capability levels, this is collated through ad-hoc training sessions for farmers and farmer groups on how to use the app (according to the availability of trainers). Once farmers are registered, they can begin requesting specific services or a bundle of services, and each transaction is recorded by the ag-platform. There is no limit to the number of service requests farmers can make on the app, but this is often subject to the ability of the farmer to pay (finance) these requests. The third phase of data collection occurs after the production stage is complete: farmers deposit their produce at a pre-determined collection point, where ag-platform representatives weigh and grade it and pay the farmer accordingly. At this stage, yield data, prices, and quality of produce are recorded for each farmer by the ag-platforms.

In sum, the data recorded includes transaction-level information, including information on key crops, different digital services requested (seeds, fertilizers, herbicides, fungicides, spray pumps, tarpaulin, tractors, good agricultural practices), yields of crops, and grades of produce; along with transaction, demographic, and socio-economic information, including gender, crop acreage, livelihood diversification, age, family size, and level of education.

Each transaction is linked to an agricultural season, which enabled us to capture issues around seasonality. The main agricultural season in Kenya is between March and August; the secondary season is between September and February. Ground truthing of data was conducted through multi-stage sampling. First, areas with the greatest farmer transaction density in each county were mapped—these being Meru, Nyeri, Trans-Nzoia, and Kakamega, which totalled about 45 per cent of the total number of transactions. A list of farmers was then generated from this map and 60 farmers (15 from each area) were randomly sampled for ground-truthing. The results were 98.33 per cent accurate, suggesting that the data have internal validity. Table A1 in the Appendix provides the numbers of male and female farmers participating on the ag-platform across all counties. Table 1 elucidates the average transactions across agricultural seasons differentiated by male and female farmers. Overarchingly, only about 35 per cent of all transactions on the platform were carried out by women.

Table 1: Transactions by men and women by agricultural season

COVID-19 occurrence	Agricultural season	% of transactions performed by women (by season total)	Men: average ratio (no. of transactions/ no. of male farmers)	Female: average ratio (no. of transactions/ no. of female farmers)	Overall average (no. of transactions/ no. of farmers)
Pre-COVID	Season 1 (March–Aug 2019)	36.54	1.511	1.497**	1.506
	Season 2 (Sept 2019–Feb 2020)	35.75	1.446	1.489*	1.461
COVID-19	Season 3 (March–Aug 2020)	38.34	2.299	1.962***	2.170
	Season 4 (Sept 2020–Feb 2021)	33.82	1.827	1.782**	1.811
	Season 5 (Feb–Aug 2021)	34.91	2.794	2.099***	2.534

Note: * significant difference at 10%, ** significant difference at 5% , *** significant difference at 1%.

Source: author's construction from own data.

Qualitative interviews were conducted after the quantitative analysis to provide further insight into the gendered effects of economic upgrading and to triangulate results. We conducted 32 semi-structured interviews: 15 women farmers, 10 male farmers, and 7 other value chain participants including Kenyan government representatives (Ministry of ICT and Ministry of Agriculture and Cooperatives), ag-platform staff, platform providers (Safaricom and input suppliers Amiran and Kenya Seeds), and civil society members (e.g. KENAFF, Maize Authority). The farmers and cooperatives/farmer groups were selected from an official list provided by the ag-platform and triangulated with our dataset to uniquely identify women farmers in areas where ground truthing was conducted. The women were selected randomly from the list and interviewed on a range of topics to dig deeper into how they engaged with ag-platforms through the pandemic. Interviews were conducted by the authors between June and August 2021.

While transaction data present many benefits, such datasets have four important limitations. First, a significant portion of the data on the app is self-reported by farmers, especially around harvesting (e.g. crop volumes produced, yields) and other demographic information (e.g., location, education, livelihoods). Second, the ag-platform works on USSD rather than android, which limits the quality and quantity of data collection, especially geo-located data. Third, ground truthing is limited by the wide geographical spread of the farmers. Fourth, the data do not effectively capture power asymmetries linked to the bargaining ability of women on prices on the ag-platform, or provide intra-household and societal information or information on public governance (e.g. when laws or domestic standards were introduced or adopted). Thus, our ability to quantitatively infer how these may affect upgrading is constrained. To partially address these limitations, a fixed effects model on location, time, and seasonality is performed and this is supplemented by qualitative interviews.

3.3 Data analysis

The paper adopts a sequential two-stage approach primarily driven by quantitative data analysis. The key question explored is: *To what extent does COVID-19 affect economic upgrading possibilities for women in platform-driven ag-value chains?* In order to reveal the granularity of implications through a shock like COVID-19, we develop three methods of unpacking the effects of COVID-19 on upgrading, which are discussed further below.

Dependent variables: economic upgrading

We build on research which examines economic upgrading in terms of crop yields, product quality, and product diversification in AVCs (like others, e.g., Barrientos 2019; Maertens and Swinnen 2009; Pasquali et al. 2021; Rao and Qaim 2011).

Crop yield: Within agriculture, productivity is often defined as partial productivity if, for example, it focuses only on crop yields (the volume of crop produced over the total land area of the crop). Many of the small farmers in our study grow multiple crops, making it complicated to disaggregate labour productivity. To allow comparison across crops, crop productivity is normalized by crop. Data normalization allows comparison of yield from different crops with potentially very different absolute yield values (Schenatto et al. 2017). For each crop–season, we calculate the yield normalized to the maximum observed yield in that season using Equation (1). This results in all seasons having normalized yield values expressed as 0 and 1.

$$Y_{norm} = Y\text{-}Y_{min}/Y_{max}\text{-}Y_{min} \tag{1}$$

where *Ynorm* is the normalized yield, *Y* the original yield of crop *A* in season *t*, and *Ymin* and *Ymax* the minimum and maximum values from the same crop yield within the dataset. The main four crops in the analysis are maize, beans, rice, and soybeans. Another benefit of yield normalization is that we no longer need to control for different crops and their properties, as the natural variation in yield originating from soil properties, other site-specific conditions (e.g. relief, hydrology), or weather is preserved in the yield data (Blasch et al. 2020).[3]

Product quality: Much of the value chain research highlights how, at the point of collection, produce is graded by actors who purchase the commodity (Krauss and Krishnan 2022; Vicol et al. 2019). This is usually done via some form of standard—be it a private standard developed and run by private firms (such as the ag-platform), a public standard set by the government, or a multi-

[3] The estimation models we use also control for unobserved heterogeneity of county. There is no need to control for different crops when considering normalized yield.

stakeholder standard set by an organization such as the Organic or Rainforest Alliance. The Kenyan ag-platform's standards relate to the size and colour of produce, marking on produce, and pesticide residue on produce. The ag-platform then 'grades' produce: Grade 1 ('best quality') referring to produce without any imperfections and following the standard set; Grade 2 having minor imperfections (e.g. a few spots on crops); and Grade 3 or 4 having significant imperfections, and therefore often rejected. We consider the proportion of the produce for each farmer that is Grade 1 and 2, which is easy for the ag-platform to sell to buyers.

Product diversification: We measure product diversification using the unweighted number of crops on which transactions occur for each farmer each year (e.g. Liu 2007). Unweighted product-count measures are reliable and have low information requirements (Van Oijen and Hendrikse 2002). An increase in 'related product diversification' across products within the same sector has been associated with increased farmer competitive advantage, and therefore with economic upgrading.

Independent variables

In the first instance, COVID-19 is seen as a homogeneous shock and therefore is a dummy variable, which takes the value 1 if in Season 3, 4, or 5, when COVID-19 was prevalent, and 0 in Season 1 or 2 , which were before COVID-19. This COVID-19 dummy is interacted with the gender dummy (which takes the value 1 for female farmers and 0 for male farmers). If the interacted coefficient is positive, it suggests that, over the seasons (time), women farmers have been able to upgrade despite the pandemic.

The second measure for COVID-19 intensity is the various regimes of the pandemic, as identified in Section 3.1, which shed light on the ever-changing implications of COVID-19 in Kenya due to different levels of uncertainty, regulation stringency, infection rates, and vaccination measures, which over time affected upgrading opportunities. The gender dummy is interacted with the regime dummy, and a positive and significant coefficient suggests that for women farmers upgrading was more likely to occur through the regimes than for men.

The third measure of COVID-19 intensity is a county-level stringency index. This was calculated using OxCGRT, which takes into account policies such as school closures, workplace closures, cancellation of public events, restrictions on gatherings, public transport closures, public information campaigns, 'stay at home' policies, restrictions on internal movement, international travel controls, testing policies, contact tracing, face covering, and vaccination plans. This composite measure is a simple additive score of the above indicators measured on an ordinal scale. This was calculated, by season, for each of the 47 counties where the ag-platform operates. The higher the values, the higher the stringency of COVID-19 measures in the particular county. Broadly, values for this indicator ranged from 18 to 20 between March and August 2020, from 22 to 23 between September 2020 and February 2021, and from 25 to 26 between March and August 2021. (See Table A2 in the Appendix for the full list of counties and COVID-19 intensity scores.) This intensity measure is also interacted with the gender dummy.

Controls

A set of control variables is included. The most important are the ag-platform governance variables, which affect how farmers are able to use and access services through the app. Relational governance is explicated through two indicators. The first is *frequency of meeting various trainers* (village agents or ag-platform employees who train farmers to use the app). The meetings develop a relational structure between farmers and ag-platform trainers through explicit training or informal discussions over queries or grievances. Such a process helps to develop networks by enabling exchange on knowledge and information, which is a key measurement for relational governance in value chains (Barrientos 2019; Gereffi 2019; Krishnan and Foster 2018; Lee and Gereffi 2011). The second measure of governance is the *stability of the relationship between farmers and ag-platform actors*. Farmers and VC actors do not act in isolation but 'within networks of relations that vary in their stability' (Morris et al. 2016: 1,249). Stable linkages between actors are critical to knowledge transfer and enhancing capabilities (Dallas 2015) and key to effective upgrading (e.g., Glückler 2005; Krishnan and Foster 2018; Pasquali et al. 2021). Drawing on Kumar and Zaheer (2019), we develop a continuous variable of network stability in the interactions between those who demand digital services (farmers) and suppliers (ag-platform), as the share of transactions of digital services in specific crops that remain the same from season *t-1* to season *t*.

In addition to the three governance variables, three other controls are used: two services indices and an information and best practice(s) dummy.

The two services indices are an input index and mechanization index, computed using tetrachoric and polychoric principal component analysis.[4] The input index consists of an array of inputs including seeds, top dressing fertilizers, planting fertilizers, herbicides, insecticides, and fungicides, while the mechanization index consists of leasing spray pumps (manual push or pull fluid tank mechanisms forcing the contents through a spray nozzle at specific gallons-per-minute flow rates and pressures), tarpaulin (heavy-duty waterproof cloth, originally of tarred canvas) to act as a greenhouse, and tractor services. Both these indices are normalized to range between 0 and 1, where values closer to 0 indicate low levels of input and mechanization demanded by farmers, while values closer to 1 report higher levels.

The information and practices dummy relates to a service that is offered by the ag-platform. Information is provided on a variety of topics, from current market prices to weather and precipitation, along with best practices on irrigation schedules, pest and diseases mitigation, and planting/harvest scheduling. This is generated as a dummy variable that takes the value 1 when any of these services is requested and 0 when none is requested.[5]

3.4 Estimation strategies: pooled OLS, FE, RE

The first estimated strategy used is pooled OLS. We first estimate the conditional correlation between female farmers with COVID-19 variable with economic upgrading (crop yields), product quality, and product diversification. This assumes that the implications on economic upgrading are homogeneous through the shock for female farmers. The second model estimates the conditional correlation between female farmers and COVID-19 regimes / economic upgrading, in effect allowing us to capture the varied effects of female farmers through the shock. And finally, for robustness, we estimate the conditional correlation of the gender dummy interacted with the county/regional stringency index with economic upgrading. We control for agricultural potential zones identified by the Ministry of Agriculture in Kenya and agricultural seasons. We also control for the other variables mentioned in Section 3.3.

The pooled OLS is followed by the estimation of fixed effects, where the fixed effects are farmer and season dummies. This is an improvement on pooled OLS, as it removes endogeneity caused

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[4] The PCA is a linear procedure (Kolenikov and Angeles 2004, 2009) and is non-robust (Huber 2003) due to distributional assumption violations, especially when it comes to the normality assumption. An alternative approach to computing correlations between ordinal variables uses assumptions similar to ordered probits (Kolenikov and Angeles 2004, 2009).

[5] As mentioned before, due to restrictions in how data are collated by the ag-platform, it is not possible to disaggregate the different types of information services.

by time-invariant omitted relevant variables such as farmers' innate risk preferences and seasonal effects. Cross-county differences that do not change over time are removed. We also use a random effects model for robustness. A Hausman test is performed to check whether random effects or fixed effects are preferred, and in all cases the fixed effects are preferred. Next, a seemingly unrelated regression is carried out, as yet another a robustness check, since error terms across crop yields, product quality, and product diversification may be related. Finally, we use quantile regressions to dig deeper into how women's upgrading differs across the distribution.

3.5 Qualitative interviews analysis

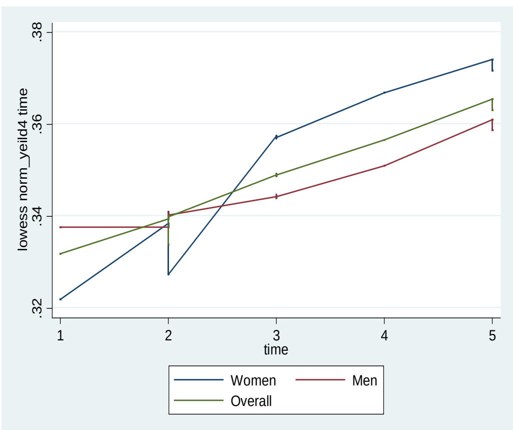
Qualitative data were collected through 20–25-minute in-depth interviews, where respondents were presented with the initial findings of the quantitative analysis and asked to discuss the implications for economic upgrading. The discussion was structured around the three dependent variables used in the quantitative analysis to define economic upgrading—i.e. crop yields, crop quality, and product diversification. Respondents were asked to discuss how COVID-19 had affected these outcomes, and whether they had experienced any improvement in their conditions of operations through the crisis (resilience). No leading questions were asked, and respondents had the freedom to mention other factors that might affect these outcomes as well. Responses were fully anonymized and organized by themes using a grounded theory approach.

4 Results

4.1 Exploratory analysis: descriptive statistics

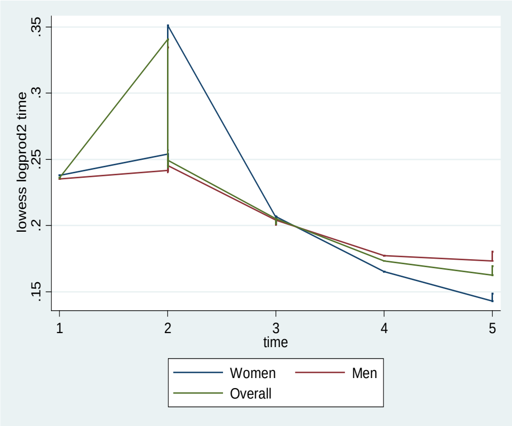
In terms of crop yields, Figure 2 illustrates that crops improved steadily over time from agriculture Seasons 1 and 2, which were pre-COVID-19, through to Seasons 3, 4, and 5, which were during COVID-19. The rate of increase of yield from Season 3 onwards for female farmers was considerably higher than that for male farmers, even though on average women's pre-COVID yields were 23 per cent lower than those of men. In terms of product quality (Figure 3), it seems that female farmers had higher crop quality (a greater proportion of Grade 1 produce) than male farmers during pre-COVID-19 seasons and that this trend continued during COVID-19. In relation to product diversification (Figure 4), the results are quite interesting. They suggest that pre-COVID-19 women attempted to increase product diversification (especially in Season 2), but there was a rapid decline through COVID-19. There was a decline for male farmers as well, but this was much more gradual.

Figure 2: log crop yields



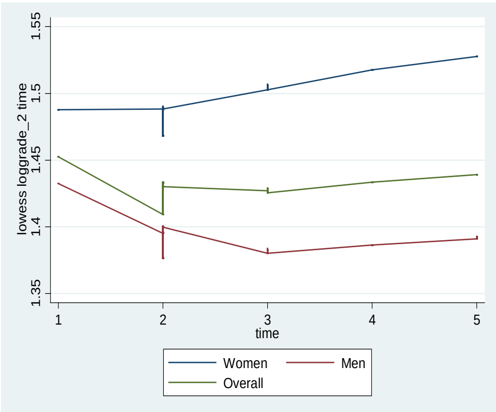
Source: authors' construction.

Figure 3: log product quality



Source: authors' construction.

Figure 4: log product diversification



Source: authors' construction.

Female and male farmers differ is several key respects. The mean differences obtained by running OLS regressions on pooled cross-section data over Seasons 1 to 5 with season-fixed effects are reported in Table 2. Women have on average higher yields than their male counterparts. Furthermore, women have significantly higher product quality, but lower product diversification compared with men. However, the difference in product diversification is insignificant.

Table 2: Differences between female and male farmers

	Variables	**Women vs men (interacted with COVID dummy)**	
		Reg. coefficients	**SE**
Dependents	Normalized yield (0–1)	.016***	.005
	Log product quality	.131***	.009
	Log product diversification	-.005	.008
Controls	COVID (dummy)	-.103***	. 005
	Relation governance (networks)	.176***	.007
	Relational governance (transaction stability)	-.037***	.006
	Input index (normalized)	.011	.007
	Mechanization index (normalized)	-.001	.001
	Information and practices	.0425***	.015

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level

Source: authors' construction.

Concerning governance variables, female farmers have lower stability of transactions than male farmers. With regard to the various services demanded, female farmers generally demand significantly more information and more practices and input services (although this is not significant) in comparison with men. (See Table A3 in the Appendix for results for the governance and other control descriptives.)

Interestingly, male and female farmers on the app have very similar levels of education, demographics, and land sizes (see Table A4 in the Appendix for a comparison of time-invariant factors), suggesting that upgrading is driven by other factors, which are explored in greater detail in the econometric analysis.

4.2 Econometric and qualitative results

Gender and COVID-19 as a homogeneous shock over time

For each dependent variable, we present three variants, which include the full specification.

Crop yields

Overall, the results shown in Table 3 suggest that women farmers have statistically lower yields than men across all models. This is consistent with many studies demonstrating similar results in Africa (e.g. Barrientos 2014; Quisumbing et al. 2014). However, surprisingly, crop yields during COVID-19 seem to increase across both male and female farmers. There is mixed anecdotal evidence to explain this. For instance, Apostolopoulos et al. (2021) find that crop yields increased for farmers on digital platforms during COVID-19 compared with those not on digital platforms in parts of Asia and Africa.

Table 3: COVID-19 and crop yields

Variables	Log normalized yield		
	POLS(1)	FE(1)	RE(1)
Gender	-.021*** (.004)		-.029*** (.004)
COVID (dummy)	0.150*** (0.005)	.048*** (.005)	.072*** (.003)
Gender*COVID	0.058*** (0.006)	.071*** (.010)	.0639*** (.005)
Log frequency of agents (relational governance)	-.003 (.004)	-.000 (.005)	-.004 (.004)
Log transaction stability (relational governance)	-.045*** (.011)	.002 (.009)	-.031*** (.007)
Input index	-.103*** (.008)	-.107*** (.012)	-.006 (.007)
Mechanization index	-.110*** (.020)	-.161*** (.042)	-.162*** (.020)
Gaps	-.010*** (.003)	-.014*** (.003)	-.005* (.003)
Constant	.282*** (.008)	.337*** (.011)	.322*** (.007)
Farmer- and time-fixed effects	Season, county	Yes (farmer, season, county)	Season, county
Observations	9,748	9,748	9,748
R-squared	0.1634***	0.2487	0.190

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' construction.

However, the interacted variable of gender and COVID-19 suggests that during COVID-19 women's crop yields increased more than those of male farmers. These results were significant across all models. This is an interesting situation, as interviews with many women farmers showed that they felt they needed to pay 'extra attention' to their crops, since they were worried they would have no other source of livelihood.

One of the factors that seemed to account for the higher crop yields was the relation between governance and transaction stability. This meant that farmers who transacted more on the platform were algorithmically seen as more 'loyal'. In relation to the various services, it appears that only input has a positive and significant effect on crop yields, while mechanization, and information and practices have a negative effect. Overarchingly, interviews suggested that during COVID-19 the types of information available were not necessarily useful, as targeted support was not provided, but the flow of inputs was key to ensuring that crops could be sown, grown, and harvested without disruption.

Product quality

Overall, the results suggest that in general women have higher product quality than men (Table 4), consistent with many other studies, as discussed in Section 2. However, there was an overall decrease in the quality of produce during COVID-19 (albeit mostly statistically insignificant). The interacted gender*COVID-19 variable is positive and statistically significant, suggesting that product quality for women rose faster than for men during COVID-19. This also implicitly suggests that most of the product quality loss occurred among male farmers. Some of the reasons cited in the interviews were that women 'cared' more for crops and felt 'responsibility' for ensuring good-quality products. Many claimed that their reputation would be affected by bad-quality produce, which would also reduce the overall margins they would get for their crops.

Table 4: COVID-19 and product quality

	Log product quality		
	POLS(1.1)	**FE(1.1)**	**RE(1.1)**
Gender	.076*** (.011)		.085*** (.010)
COVID (dummy)	-.006 (.012)	-.016 (.021)	-.021** (.009)
Gender*COVID	.055*** (.013)	.023* (.013)	.055*** (.013)
Log frequency of agents (relational governance)	-.010 (.009)	-.021 (.016)	-.014 (.009)
Log transaction stability (relational governance)	-.007 (.021)	-.013 (.033)	-.023 (.017)
Input index	.169** (.016)	-.007 (.036)	.166*** (.015)
Mechanization index	.055 (.047)	-.171 (.126)	.068 (.045)
Gaps	-.047*** (.009)	-.010* (.003)	-.039** (.008)
Constant	1.437*** (.019)	1.476*** (.034)	1.426*** (.017)
Farmer- and time-fixed effects	Season, county	Yes (farmer, season, county)	Season, county
Observations	9,748	9,748	9,748
R-squared	0.040	0.002	

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' construction.

Interestingly, in this case relational governance—i.e. strong and loyal networks with the ag-platform—does not seem to have a statistically significant effect on product quality. But like crop yields, inputs have a positive and significant effect on product quality. Again, this is important, as many of the farmers mentioned that the ag-platform was a key means of access to various inputs during the crisis, in view of supply chain shortages and curfews.

Product diversification

The results shown in Table 5 suggest that, in general, women have higher product diversification than men, which has been shown across a few studies. Huang et al. (2014), for instance, found that women diversify more than men; but Barrientos (2014, 2019) suggested the opposite. The results also suggest a downward trend in product diversification during COVID-19 across both male and female farmers, signalling product concentration. The interacted gender*COVID-19 dummy highlights that female farmers reduced product diversification (increased concentration) more than male farmers during COVID-19. Interviews with female farmers revealed their perception that, through COVID-19, focusing on a few crops would be a less risky strategy than spreading themselves too thinly across many less risky crops. The situation was seen in a very different light by male farmers, who mostly claimed that increasing the number of crops they grew would be a better hedge during COVID-19.

Table 5: COVID-19 and product diversification

	Log product diversification		
	POLS(1.2)	**FE(1.2)**	**RE(1.2)**
Gender	.016** (.006)		.017*** (.004)
COVID (dummy)	-.095*** (.007)	-.004*** (.001)	-.032*** (.002)
Gender*COVID	-.005* (.001)	-.021*** (.002)	-.014*** (.003)
Log frequency of agents (relational governance)	-.021*** (.007)	-.008*** (.002)	-.007*** (.002)
Log transaction stability (relational governance)	.168*** (.017)	.007* (.004)	.006 (.004)
Input index	-.121*** (.010)	.021*** (.006)	-.011** (.005)
Mechanization index	-.341*** (.034)	.014 (.017)	-.085*** (.019)
Gaps	-.033*** (.005)	-.002 (.001)	-.003* (.001)
Constant	.333*** (014)	.236*** (.004)	.205*** (.004)
Farmer- and time-fixed effects	Season, county	Yes (farmer, season, county)	Season, county
Observations	9,748	9,748	9,748
R-squared	0.1573	0.0343	0.1456

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' construction.

Another interesting point to note here is related to governance: that it is especially the rate of transaction stability that engenders increased product diversification, but having strong networks with the ag-platform itself leads to more product concentration. This means that product diversification depends less on how the chain is governed and is much more an individual strategy that farmers take, more broadly, to hedge against risks like COVID-19.

In terms of the services index, overall the results suggest that even with a higher number of inputs and more mechanization and good practices information, there was mostly product concentration rather than diversification. This could partly be attributed to the types of inputs and information dissemination that took place during the pandemic. Some interviews with the ag-platform and various SHG members suggested that most of the information that was shared with farmers related to ensuring crop health, and not as much to growing multiple crops simultaneously.

Gender and COVID-19 intensity over time

Crop yield

The results in POLS(2), FE(2), and RE(2) include the regimes of COVID-19, as discussed in Section 3, while POLS(3), FE(3), and RE(3) include the COVID-19 regional intensity index, calculated at county level. We are concerned here only with the results for the interaction term gender*regimes, so as to show the varied implications for female farmers through the different regimes of COVID-19. The results shown in Table 6 suggest that, across all three regimes of the pandemic, there was an increase in yields compared with pre-pandemic levels. The coefficient is positive and statistically significant across all models, suggesting that the results are robust. Furthermore, it is interesting to note that, during the time of peak fear (Regime 1), yields increased for women (gen*regimes) compared both with pre-pandemic levels and with male farmers, before dipping slightly in Regime 2 and then increasing again in Regime 3. Overall, this suggests that women were able to continue to upgrade in terms of yield through the pandemic, and even to exceed pre-pandemic levels.

When we look at the results through the regional intensity lens, a similar picture arises, suggesting that, even as regional stringency increased during COVID-19, women were still able to outperform men in terms of generating higher yields, across all models.

Product quality

The results for product quality (Table 7) suggest that, overarchingly, product quality decreased through the pandemic. However, the interaction term shows that product quality has an upward trend for female farmers through the COVID-19 regimes across all models (barring Regime 2 in FE, which is insignificant). Overall, this suggests that women were able to continue to upgrade in terms of product quality through the pandemic, and even to exceed pre-pandemic levels.

When looking at the results through the regional intensity lens, a similar picture emerges, suggesting that, even as regional stringency increased, women were still able to outperform men in terms of higher product quality, across all models.

Product diversification

The results for product quality (Table 8) suggest that, overarchingly, product diversification decreased through the COVID-19 regimes, especially for female farmers. Broadly, the interaction term shows that female farmers tend to have a higher diversification in Regime 1 than men (and pre-COVID), but this falls drastically in Regime 2 and even more in Regime 3 compared with men (and with pre-COVID levels). This suggests that downgrading occurred through the pandemic.

When looking at the results through the regional intensity lens, a similar picture emerges, suggesting that, as regional stringency increased, women underperformed men in terms of product diversification, i.e. instead, product concentration or contraction occurred, across all models. As a robustness check, because yields, product quality, and product diversification may be inter-related, tests using seemingly unrelated regressions to account for variation with the agricultural seasons were run, and the results hold (see Table A5 in the Appendix). Thus, the above models are robust.

Table 6: COVID-19 regimes and crop yields

	Log normalized yields					
	POLS(2)	**POLS(3)**	**FE(2)**	**FE(3)**	**RE(2)**	**RE(3)**
Gender	-.022***	-.020***			-.029***	-.027***
	(.004)	(.004)			(.004)	(.004)
Regime 1 (compared with Regime 0)	.127***		.039***		.057***	
	(.037)		(.005)		(.003)	
Regime 2 (compared with Regime 0)	.140***		.028***		.052***	
	(.019)		(.006)		(.004)	
Regime 3 (compared with Regime 0)	.138***		.092***		.115***	
	(.006)		(.007)		(.005)	
Gender*regime 1 (compared with	.063***		.079***		.069***	
Regime 0)	(.007)		(.010)		(.006)	
Gender*regime 2 (compared with	.043***		.047***		.046***	
Regime 0)	(.010)		(.012)		(.008)	
Gender*regime 3 (compared with	.054***		.079***		.066***	
Regime 0)	(.010)		(.016)		(.009)	
Gender*log regional COVID intensity		.029		.036***		.033***
		(.003)***		(.003)		(.003)
Log regional COVID intensity		-.074		.030***		.040***
		(.187)		(.002)		(.001)
Log frequency of agents (relational	-.002	-.005	.001	-.003	-.004	-.007*
governance)	(.004)	(.004)	(.005)	(.005)	(.004)	(.003)
Log transaction stability (relational	-.044***	-.044***	-.002	.006	-.033***	-.029***
governance)	(.011)	(.011)	(.008)	(.009)	(.007)	(.007)
Information and practices	-.010***	-.010***	-.012***	-.014***	-.005*	-.005*
	(.003)	(.003)	(.003)	(.003)	(.002)	(.002)
Mechanization index	-.112***	-.112***	-.133***	-.154***	-.144***	-.156***
	(.020)	(.020)	(.041)	(.041)	(.020)	(.020)
Input index	.096***	.095***	-.097***	-.101***	.000*	-.004
	(.007)	(.007)	(.012)	(.012)	(.007)	(.007)
Constant	.282***	.287***	.328***	.336***	.319***	.323***
	(.008)	(.008)	(.011)	(.011)	(.007)	(.007)
Farmer- and time-fixed effects	Season, county	Yes (farmer, season, county)	Season, county	Season, county	Farmer, season, county	Season, county
Observations	9,748	9,748	9,748	9,748	9,748	9,748
R-squared	0.1649	0.1643	0.3168	0.2655	0.2639	0.2114

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' calculations.

Table 7: COVID-19 regimes and product quality

	Log product quality					
	POLS(4)	**POLS(5)**	**FE(4)**	**FE(5)**	**RE(4)**	**RE(5)**
Gender	.076***	.077***			.086***	.086***
	(.011)	(.011)			(.010)	(.010)
Regime 1 (compared with Regime 0)	.045		-.038*		-.026**	
	(.073)		(.021)		(.010)	
Regime 2 (compared with Regime 0)	-.020		-.010		-.026*	
	(.045)		(.030)		(.014)	
Regime 3 (compared with Regime 0)	-.029**		.033		-.004	
	(.014)		(.027)		(.013)	
Gender*regime 1 (compared with	.048***		.039*		.049***	
Regime 0)	(.015)		(.016)		(.015)	
Gender*regime 2 (compared with	.049**		-.001		.054**	
Regime 0)	(.024)		(.048)		(.023)	
Gender*regime 3 (compared with	.065***		.006*		.070***	
Regime 0)	(.019)		(.001)		(.019	
Gender*log regional COVID intensity		.030***		.022**		.029**
		(.007)		(.007)		(.007)
Log regional COVID intensity		-2.105***		-.105***		-.009***
		(.393)		(.011)		(.004)
Log frequency of agents (relational	-.013	-.012	-.013	-.026*	-.016*	-.017**
governance)	(.010)	(.009)	(.016)	(.014)	(.009)	(.008)
Log transaction stability (relational	-.007	-.014	-.005	-.010	-.023	-.024
governance)	(.021)	(.021)	(.034)	(.033)	(.017)	(.017)
Information and practices	-.047***	-.045***	.011	.011	-.040***	-.039***
	(.009)	(.009)	(.014)	(.014)	(.008)	(.008)
Mechanization index	.055	.047	-.144	-.169	.075*	.069
	(.047)	(.046)	(.126)	(.126)	(.045)	(.045)
Input index	.153***	.149***	.006	-.005	.170***	.166***
	(.014)	(.014)	(.036)	(.036)	(.015)	(.015)
Constant	1.446***	1.449***	1.455***	1.480***	1.429***	1.429***
	(.019)	(.018)	(.035)	(.035)	(.018)	(.017)
Farmer- and time-fixed effects	Season, county	Yes (farmer, season, county)	Season, county	Season, county	Farmer, season, county	Season, county
Observations	9,748	9,748	9,748	9,748	9,748	9,748
R-squared	0.0413	0.0441	0.0082	0.0022		

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' calculations.

Table 8: COVID-19 regimes and product diversification

	Log product diversification					
	POLS(6)	**POLS(7)**	**FE(6)**	**FE(7)**	**RE(6)**	**RE(7)**
Gender	.015**	.017***			.016***	.023***
	(.006)	(.006)			(.004)	(.004)
Regime 1 (compared with Regime 0)	.110*		-.001**		-.024***	
	(.058)		(.000)		(.001)	
Regime 2 (compared with Regime 0)	-.027		-.001		-.024***	
	(.027)		(.000)		(.002)	
Regime 3 (compared with Regime 0)	-.076***		-.001		-.027***	
	(.007)		(.000)		(.002)	
Gender*regime 1 (compared with	.003		.016***		.019***	
Regime 0)	(.009)		(.003)		(.003)	
Gender*regime 2 (compared with	.001		-.067***		-.057***	
Regime 0)	(.016)		(.008)		(.008)	
Gender*regime 3 (compared with	-.024**		-.000***		-.090***	
Regime 0)	(.012)		(.009)		(.008)	
Gender*log regional COVID intensity		-.023**		-.020***		-.014***
		(.004)		(.001)		(.002)
Log regional COVID intensity		-.176**		.001***		-.017***
		(.064)		(.000)		(.001)
Log frequency of agents (relational	-.018**	-.020***	.004**	-.005**	.003*	-.005***
governance)	(.007)	(.007)	(.001)	(.002)	(.002)	(.002)
Log transaction stability (relational	.166***	.166***	-.000	.005	-.000	.004
governance)	(.017)	(.017)	(.003)	(.004)	(.003)	(.004)
Information and practices	-.033***	-.033***	-.000	-.002	-.001	-.002
	(.005)	(.005)	(.001)	(.001)	(.001)	(.001)
Mechanization index	-.338***	-.339***	-.003	.012	-.068**	-.087***
	(.033)	(.034)	(.011)	(.016)	(.014)	(.019)
Input index	-.112***	-.114***	.009**	.018***	-.010***	-.013**
	(.009)	(.009)	(.004)	(.006)	(.004)	(.005)
Constant	.328***	.332***	.218***	.235***	.178***	.202***
	(.014)	(.014)	(.003)	(.004)	(.004)	(.004)
Farmer- and time-fixed effects						
Observations	9,748	9,748	9,748	9,748	9,748	9,748
R-squared	0.1605	0.1585	0.4278	0.0677	0.3701	

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' calculations.

4.3 Quantile regressions

The data in this section dig deeper into women's upgrading. Since upgrading occurred only in yield and product quality, we only unpack the different upgrading implications across women in relation to yield and quality, i.e. the quantile regression results indicate the implications on women during COVID-19 through the percentiles. All regressions include fixed effects, so are robust to cross-county heterogeneity. Column (1) is at the 10th percentile, (2) the 25th, (3) the median, (4) the 75th percentile, and (5) the 90th percentile. The results are shown in Table 9.

With regard to crop yield, an interesting insight emerges: the coefficients of gender*COVID-19 are all significant and positive across the distribution, and increase until the 50th percentile, after which there is a plateauing and a fall by the 90th percentile, suggesting an inverted U curve. This means that women during COVID-19 had higher yields at an increasing rate, but this rate of increase decreases as we go through the distribution. Briefly, the results indicate that relational governance has a negative coefficient, and the negative value increases through the percentiles. The results of governance (transaction stability) are also interesting, as there is a negative relationship between stability and yields, until the 75th percentile, after which it turns positive and significant.

The results for product quality are more undulating. While the coefficient is positive and significant across the distribution, the lower percentiles (10 and 50) have the most positive coefficients, and the coefficient consistently reduces as we move from the 50th to the 90th percentile. There seems to be a peak around the 50th percentile. Overall, this means that at the higher percentiles women during COVID-19 have higher product quality than men, but less so than women in the 50th percentile.

Table 9: Quantile regressions

	Log normalized yield					Log product quality				
Variables/Percentiles	10	25	50	75	90	10	25	50	75	90
Gender*COVID	0.026***	0.038***	0.060***	0.062***	0.038***	0.271***	0.083***	0.125***	0.062***	.036***
	(.002)	.005	.005	.003	.012	(.027)	0.029	.010	.005	(.009)
COVID (dummy)	0.001	0.001	-0.002	0.013***	.025***	-.144***	-0.067***	-0.040***	-0.047***	-.042***
	(0.003)	.004	.005	.003	(.007)	(.024)	0.020	.013	.004	(.005)
Input index	0.084***	0.224***	0.108***	0.065***	.089***	.194***	-0.005	-0.002	-0.001	.082***
	(.015)	.016	.009	.009	(.029)	(.053)	.016	.031	.014	(.023)
Mechanization index	-0.011	-0.033	-0.095***	-0.135***	-0.217***	.305***	0.055	0.052	-0.192***	-.249***
	(.026)	.024	.025	.020	(.036)	(.106)	.045	.080	.037	(.048)
Information and practices	-0.007 (0.004)	-0.008	-0.014***	-0.020***	-0.014*	.169***	0.077***	0.085***	0.026***	.026***
		.007	.004	.003	(0.007)	(.040)	.025	.014	.006	(.008)
Log stability	-0.088***	-0.242***	-0.156***	-0.104**	-0.116***	.125***	-0.012	0.006	0.027**	.039***
	(0.005)	.011	.009	.008	(0.016)	(.038)	.018	.021	.012	(.009)
Log freqency agents	-0.016***	-0.046***	-0.038***	-0.018**	0.011	.233***	-0.022	-0.141***	-0.088***	-.037***
	(0.004)	.007	.016	.008	(0.025)	(.034)	.029	.031	.018	(.013)
Constant	0.172***	0.298***	0.432***	.464***	.558***	.820***	1.295***	1.459***	1.688***	1.769***
	(0.004)	.009	.005	.005	(0.013)	(.034)	.007	.014	.008	(.009)
Observations	9,748	9,748	9,748	9,748	9,748	9,748	9,748	9,748	9,748	9,748

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Source: authors' calculations.

5 Discussion and conclusion

This paper attempted to unpack the intersection of gender and upgrading in a digital value chain context through a shock (the COIVD-19 pandemic). The data suggest that women are able to economically upgrade in terms of crop yields and product quality, while they tend to downgrade in relation to product diversification. When delving deeper, we find that women outperformed men in crop yields through the pandemic and were able to considerably increase their yields over pre-pandemic levels. Across the various regimes, there was a steady improvement in yields, despite lockdowns and other stringent measures. Furthermore, female farmers were able to continue to improve product quality, which was seen as an important strategy for coping with the effects of COVID-19, and this also occurred through the pandemic, albeit dipping slightly in Regime 2. Thus, it is critical to note that there are indeed heterogeneous ways in which women upgrade through the pandemic, and that living through a shock seems to have brought some level of positive change for women.

However, women's downgrading in relation to product diversification is an interesting case. Interviews with many female farmers suggest that product concentration was a strategy they chose to pursue rather than something that was forced on them by circumstances. This was contrary to the strategy that men followed, alluding to a difference in risk profiles and preferences. Further research is needed to delve deeper into the varied cognitive reasons that such strategies are selected.

An important insight this paper throws up is that relational governance during shocks—especially in relation to stronger links with the ag-platform—does not seem to matter very much; however, loyalty (transaction stability) does to some extent, facilitating upgrading possibilities. This is contrary to the broader literature within GVCs, which alludes to the pivotal role played by the private sector. However, broader issues around supply chain shocks, curfews, and governmental pressures, which we account for through our regimes, together with our regional stringency calculations tell a different story—one that generally has negative implications across all economic upgrades. Interviews with farmers suggest that the negative implications of these outweigh any positive experiences of relational governance structures. Further research is required to delve deeper into the reasons for this.

In sum, this paper elucidates the importance of looking at shocks heterogeneously, across regimes, as the implications vary over time, rather than assuming a simple positive or negative effect across the entirety of a shock. Furthermore, the research points to the ability of women to cope and overcome shocks.

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Appendix

Table A1: Dis-aggregation of male and female farmers participating in the ag-platform by county (numbers)

	Male (no.)	Female (no.)	Total (no.)	Ratio (male to female)
Baringo	58	71	129	0.817
Bomet	523	218	741	2.399
Bungoma	158	111	269	1.423
Busia	144	78	222	1.846
Elgeyo-marakwet	12	12	24	1.000
Embu	34	22	56	1.545
Garissa	71	6	77	11.833
Homa Bay	56	6	62	9.333
Isiolo	13	5	18	2.600
Kajiado	20	9	29	2.222
Kakamega	457	532	989	0.859
Kericho	169	112	281	1.509
Kiambu	135	31	166	4.355
Kilifi	13	10	23	1.300
Kirinyaga	30	3	33	10.000
Kisii	168	53	221	3.170
Kisumu	209	75	284	2.787
Kitui	70	57	127	1.228
Kwale	14	1	15	14.000
Laikipia	1,040	159	1,199	6.541
Lamu	2	0	2	NA
Machakos	95	35	130	2.714
Makueni	70	16	86	4.375
Mandera	51	6	57	8.500
Marsabit	1	3	4	0.333
Meru	1,152	1,373	2,525	0.839
Migori	80	27	107	2.963
Mombasa	38	37	75	1.027
Murang'a	221	39	260	5.667
Nairobi	173	94	267	1.840
Nakuru	372	223	595	1.668
Nandi	94	42	136	2.238
Narok	365	98	463	3.724
Nyamira	30	32	62	0.938
Nyandarua	56	20	76	2.800
Nyeri	1,036	138	1,174	7.507
Samburu	5	1	6	5.000
Siaya	78	9	87	8.667
Taita Taveta	21	7	28	3.000
Tana River	9	3	12	3.000
Tharaka Nithi	53	24	77	2.208
Trans-nzoia	621	411	1,032	1.511
Turkana	25	12	37	2.083
Uasin Gishu	349	142	491	2.458
Vihiga	110	134	244	0.821
Wajir	59	7	66	8.429
West Pokot	15	12	27	1.250

Source: authors' construction.

Table A2: COVID-19 intensity scores by county

County	March–Aug 2019	Sept 2019–Feb 2020	March–Aug 2020	Sept 2020–Feb 2021	March–Aug 2021
Baringo	0	0	20	22.66666667	25.33333333
Bomet	0	0	20	22.66666667	26
Bugoma	0	0	20	22.66666667	26.33333333
Busia	0	0	18.33333333	22	26.33333333
Elgeyo-marakwet	0	0	18.33333333	22	26.33333333
Embu	0	0	20	22.66666667	26.33333333
Garissa	0	0	18.33333333	22	26.33333333
Homo Bay	0	0	18.33333333	22	26.33333333
Isiolo	0	0	18.33333333	22	26.33333333
Kajiado	0	0	18.33333333	22	26.33333333
Kakamega	0	0	20	23.33333333	26.33333333
Kericho	0	0	20	23.33333333	26.33333333
Kiambu	0	0	20	23.33333333	26.33333333
Kilifi	0	0	20	23.33333333	27
Kirinyaga	0	0	20	23.33333333	26.66666667
Kisii	0	0	18.33333333	22	25.66666667
Kisumu	0	0	20	23.33333333	26.66666667
Kitui	0	0	18.33333333	22	25.66666667
Kwale	0	0	18.33333333	22	25.66666667
Laikipia	0	0	18.33333333	22	25.66666667
Lamu	0	0	18.33333333	22	25.66666667
Machakos	0	0	19	23	26.33333333
Makueni	0	0	18.33333333	22	25.66666667
Mandera	0	0	18.33333333	22	25.66666667
Marsabit	0	0	18.33333333	22	25.66666667
Meru	0	0	18.33333333	22	25.66666667
Migori	0	0	19	22	25.66666667
Mombasa	0	0	19	22	25.66666667
Murang'a	0	0	18.33333333	22	25.66666667
Nairobi	0	0	19.33333333	23	26.33333333
Nakuru	0	0	20	23	26.33333333
Nandi	0	0	19	22	25.66666667
Narok	0	0	19	22	25.66666667
Nyamira	0	0	19	22	25.66666667
Nyandarua	0	0	19	22	25.66666667
Nyeri	0	0	19	22	25
Samburu	0	0	18.33333333	22	25.66666667
Siaya	0	0	18.33333333	22	25.66666667
Taita Taveta	0	0	18.33333333	22	25.66666667
Tana River	0	0	18.33333333	22	25.66666667
Tharaka Nithi	0	0	18.33333333	22	25.66666667
Trans-zoia	0	0	19	22	25
Turkana	0	0	18.33333333	22	25.66666667
Usian Gishu	0	0	19	22	25
Vihigia	0	0	19	22	25.33333333
West Pokot	0	0	18.33333333	22	25.66666667
Wajir	0	0	18.33333333	22	25.66666667

Source: authors' construction.

Table A3: Governance and other control descriptives

	Pre-COVID-19						COVID-19					
	Male		**Female**		**Overall**		**Male**		**Female**		**Overall**	
Variables/ descriptive	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Log transactions (stability)	1.208	0.010	1.174**	0.013	1.196	0.008	1.575[a]	0.028	1.366***[a]	0.023	1.499	0.020
Input index (0–1)	0.210	0.004	0.173	0.005	0.196	0.003	0.234	0.004	0.245	0.006	0.238	0.003
Mechanization index (0–1)	0.025	0.001	0.026	0.002	0.026	0.001	0.024	0.001	0.022	0.001	0.024	0.001
GAP (0–1)	0.255	0.008	0.227	0.010	0.245	0.006	0.463	0.009	0.454	0.012	0.460	0.007

Note: **significant difference at 5%; *** significant at 1% (between male and female farmers); [a] significant at 1% across male and female farmers pre-COVID-19 and COVID-19.

Source: authors' construction.

Table A4: Time-invariant factors

	Male		**Female**		**Overall**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Land size (acres)	3.696	0.227	3.359	0.101	3.482	0.104
Land under crops (acres)	1.365	0.086	1.233*	0.039	1.281	0.040
Family size	4.072	0.029	4.072	0.038	4.072	0.023
Education (years)	5.567	0.028	5.594	0.034	5.577	0.022
Age (years)	44.366	0.235	44.691	0.309	44.483	0.187
Livelihood diversification	0.820	0.004	0.833	0.006	0.825	0.003

Source: authors' construction.

Table A5: Seemingly unrelated regressions for robustness

	Log normalized yield	**Log product quality**	**Log product diversification**
Gender	-.022***	.076***	.015***
	(.003)	(.011)	(.005)
Regime 1 (compared with Regime 0)	.127***	.045	.110*
	(.035)	(.073)	(.060)
Regime 2 (compared with Regime 0)	.140***	-.020	-.027
	(.023)	(.044)	(.029)
Regime 3 (compared with Regime 0)	.138***	-.029**	-.078*
	(.006)	(.014)	(.013)
Gender*regime 1 (compared with Regime 0)	.063***	.048***	.003
	(.008)	(.015)	(.009)
Gender*regime 2 (compared with Regime 0)	.043***	.049**	.001
	(.014)	(.017)	(.117)
Gender*regime 3 (compared with Regime 0)	.058***	.065***	-.024*
	(.013)	(.019)	(.013)
Log frequency of agents (relational governance)	-.002	-.013	-.018***
	(.004)	(.012)	(.006)
Log transaction stability (relational governance)	-.044***	-.007	.166***
	(.009)	(.017)	(.014)
Input Index	.096***	.155***	-.112***
	(.008)	(.011)	(.007)
Mechanization index	-.112***	.055	-.338***
	(.019)	(.047)	(.029)
Information and practices	-.010***	-.047***	-.333***
	(.003)	(.026)	(.005)
constant	.282***	1.446***	.328***
	(.008)	(.019)	(.014)
R-sq	0.164	.041	.163
Chi^2	1925.13***	419.44***	1863.44***

Source: authors' construction.