The impact of unifying agricultural wholesale markets on prices and farmers' profitability

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Edited by David Zilberman, University of California, Berkeley, CA, and approved December 23, 2019 (received for review April 26, 2019)

As a leading effort to improve the welfare of smallholder farmers, several governments have led major reforms in improving market access for these farmers through online agricultural platforms. Leveraging collaboration with the state government of Karnataka, India, this paper provides an empirical assessment on the impact of such a reform—implementation of the Unified Market Platform (UMP)—on market prices and farmers' profitability. UMP was created in 2014 to unify all trades in the agricultural wholesale markets of the state to be carried out within a single platform. By November 2019, 62.8 million metric tons of commodities valued at $21.7 billion (USD) have been traded on UMP. Employing a difference-in-differences method, we demonstrate that the impact of UMP on modal prices varies substantially across commodities. In particular, the implementation of UMP has yielded an average 5.1%, 3.6%, and 3.5% increase in the modal prices of paddy, groundnut, and maize. Furthermore, UMP has generated a greater benefit for farmers who produce higher-quality commodities. Given low profit margins of smallholder farmers (2 to 9%), the range of profit improvement is significant (36 to 159%). In contrast, UMP has no statistically significant impact on the modal prices of cotton, green gram, or tur. Using detailed market data from UMP, we analyze how features related to logistical challenges, bidding efficiency, in-market concentration, and the price discovery process differ between commodities with and without a significant price increase due to UMP. These analyses lead to several policy insights regarding the design of similar agri-platforms in developing countries.

impact assessment | poverty reduction | smallholder farmers | market reform | developing countries

Agriculture plays a significant role in the economies of most developing countries. As ref. 1 notes, "Of the developing world's 5.5 billion people, 3 billion live in rural areas, nearly half of humanity. Of these rural inhabitants, an estimated 2.5 billion are in households involved in agriculture, and 1.5 billion are in smallholder households." Sadly, smallholder farmers in developing countries persistently struggle with poverty, in part due to unfavorable market outcomes for these farmers. Prior studies have examined various factors affecting farmers' revenue in traditional markets of developing economies. These include imperfect competition (2), provision of market information or the lack thereof (3–6), logistical infrastructure (7), and limited market access (8).

To address these challenges, one approach that has been attracting substantial investment is to connect geographically distributed agri-markets through a single online agri-platform. The hope is that integrating geographically distant markets within a common platform can increase market competition, enable transparency of the price discovery process, and ultimately, improve farmers' profitability. For example, The World Bank has invested $4.2 billion between 2003 and 2010 to develop infrastructure for information and communication technologies in the developing world (9). Various countries have launched online agri-platforms to transform traditional markets, with prominent examples such as the Ethiopia Commodity Exchange (ECX) and the *e*National Agriculture Market (eNAM) in India. While it is postulated that building online agri-platforms can benefit farmers for the aforementioned reasons, rigorous empirical evidence is limited. Furthermore, qualitative evidence has suggested mixed results for some of the existing platforms (10, 11). To fill this gap, this paper offers an econometric analysis that evaluates the impact of launching such a platform—the Unified Market Platform (UMP) in Karnataka, India—on farmers' profitability.

UMP was established in 2014 by the state government of Karnataka to unify all transactions occurring in the state's regulated agricultural wholesale markets to be carried out within a single online platform. By November 2019, 162 of the 164 regulated markets across 30 districts in the state have been integrated to UMP, and ∼62.8 million metric tons of commodities valued at $21.7 billion (USD) have been traded on the platform. Therefore, it is of significant value to empirically evaluate whether and how much the implementation of this statewide agri-platform has impacted market prices and farmers' profitability. In addition, we utilize the analysis to shed light on systemic features that should be carefully considered in

Significance

To improve smallholder farmers' welfare, several governments have led reforms in improving market access for these farmers through online agri-platforms. This paper empirically evaluates the impact of such a reform—the Unified Market Platform (UMP) in Karnataka, India—on market prices and farmers' profitability. The analysis shows an average 5.1%, 3.6%, and 3.5% increase in the modal prices of paddy, groundnut, and maize due to UMP. However, the analysis also indicates a lack of statistically significant impact on the modal prices of cotton, green gram, and tur. We provide evidence that commodities with a significant price increase differ from those without systemic features related to logistical challenges, bidding efficiency, in-market concentration, and the price discovery process used.

Author contributions: R.L., M.R., S.S., and Y.Z. designed research, performed research, contributed new reagents/analytic tools, analyzed data, and wrote the paper.

Competing interest statement: M.R. is the Managing Director & CEO of Rashtriya e Market Services Private Limited.

This article is a PNAS Direct Submission.

Data deposition: Data source 3 was obtained under a nondisclosure agreement with ReMS and can be obtained at Harvard Dataverse, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/O19FOR.

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This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1906854117/-/DCSupplemental.

First published January 21, 2020.

the design and implementation of other agri-platforms around the world.

Traditional Markets versus UMP

India's agricultural regulations in many states require that the trading of a predefined set of agricultural commodities be conducted in regulated agricultural markets called "mandis." The process starts with farmers bringing their commodities to a commission agent of their choice in their local mandi. Traders in the mandi visit commission agent shops, examine the quality of the commodities, and engage in auctions or direct negotiations to purchase the commodities of interest. Each trade is typically for a single "lot" from one farmer. Once the trade is finalized, commodities in the lot are weighed, and the winning trader pays the total price plus a commission to the agent, who later pays the farmer.

While the regulations were enacted to protect farmers' welfare, the resulting market structure and trade process have led to poor outcomes for farmers (12). First, lack of transportation and storage capabilities limit farmers' sales channels to the local mandis nearby. Second, since traders need to apply for a separate license for each mandi, there are typically a small number of traders participating in each mandi. Furthermore, the traders' demand (from their customers) predominantly occurs during harvest seasons when supply quantity is high, and hence traders engage in active trading mostly during those times. Third, the price-setting process in the mandis is done through handwritten tender slips and is not documented. It is subject to collusions among traders and also often involves private negotiations between the commission agents and the traders. Taken together, the restricted market access, their weak market power, and the nontransparent price discovery process all contribute to low sale prices and poor revenue for the farmers.

Realizing these challenges, the state government of Karnataka established the Rashtriya e Market Services Private Limited (ReMS) in 2014 and tasked this organization to integrate and digitize all mandis in the state through a single online platform—UMP. Under this reform, a number of changes were made to the traditional process (13). First, the open outcry ascending auction is replaced by the online first-price sealed-bid auction. Traders must submit their (private) bids for all of the lots they want to purchase on UMP by a preannounced cutoff time. Once the submission window is closed, all bids for the same lot are compared by the computer and the highest bidder is declared the winner. Second, all lots arriving at any of the integrated mandis are recorded on UMP and visible to all traders. Furthermore, the government enacted a single-license system so that traders need only one license to trade in all mandis within the state. Therefore, traders can now bid for lots that are put up for sale in other mandis. The process of generating transport permits and bills has also been digitized to facilitate the posttrade processes for traders. Finally, to increase price transparency for farmers, the government 1) installed computer kiosks where farmers can check prices in major mandis across the state and 2) started sending short message service (SMS) messages to farmers informing them of the winning bid for their lots.

The government believes that these changes can benefit farmers through two main mechanisms—increased competition among the traders and improved transparency. The hope is that both in-market and cross-market competition would increase because 1) traders can participate in cross-market trading with a single license and 2) moving to sealed-bid auctions online and automating many of the posttrade processes can increase traders' efficiency. In the meantime, price transparency benefits farmers because it helps to increase farmers' bargaining power compared to the traditional process. Nevertheless, the key question is, Have these expected mechanisms been effective in improving prices for farmers?

Data and Empirical Approach

We employ a difference-in-differences (DID) approach for our analysis (Eq. **1**). All markets in Karnataka, once integrated into UMP, are taken as treatment markets, and all markets outside of Karnataka are taken as control markets. The analysis focuses on six commodities for which 1) we have sufficient numbers of both treatment and control markets and 2) a common linear pretrend of prices between the treatment and control markets prior to UMP's implementation cannot be rejected in the parallel trend test. These commodities are cotton, green gram, groundnut, maize, paddy, and tur. See Materials and Methods and *SI Appendix, Data Processing* for more details.

We utilize both public data from the Government of India and lot-level data from UMP in our analysis. There are three major data sources: 1) daily modal, maximum, and minimum prices and supply quantity data for multiple commodities in all regulated mandis across India from 2012 to 2017 published by the Government of India; 2) district- and state-level demographic, socioeconomic, and rainfall data from 2012 to 2017 published by government agencies; and 3) dates of UMP implementation across Karnataka mandis and lot-level auction data on UMP from 2016 to 2018. We aggregate the daily price and quantity data to the weekly level for the analysis because different markets are open on different days of the week. Data source 2 is used to construct various covariates to control for potential differences across markets, including monthly rainfall from current to 6 mo prior, yearly total production, and yearly yield, all at the district level, and per capita GDP at the state level. We map each market to the associated district and state to match these covariates to the market level. The lot-level data from UMP is used to analyze systemic features that may differ across different commodities. See *SI Appendix, Data Processing* for more details.

The Impact of UMP

Fig. 1 illustrates the estimated average impact of UMP on the modal prices of the six commodities, ordered by the magnitude of the impact from top to bottom. The statistics are summarized in the "main model" column in Table 1. We observe that the implementation of UMP has yielded statistically significant, positive impacts on the modal prices of paddy, groundnut, and maize—a 5.1%, 3.6%, and 3.5% increase. Given low profit margins for smallholder farmers (2 to 9%), these price increases imply 36 to 159% improvement in the profit margins for over 2 million farmers who traded on

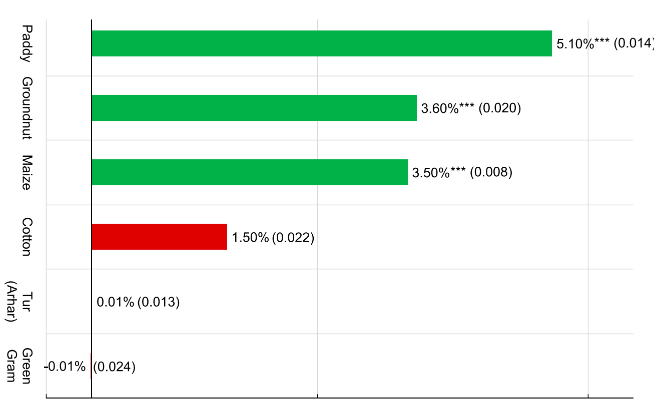

Fig. 1. Estimated average impact (in percent) of UMP on the modal prices of different commodities from the main model (Eq. **1**). Green (red) indicates a statistically significant (nonsignificant) impact. Numbers next to the bars are the estimates with standard errors in parentheses.

Table 1. Estimated impact of the UMP by commodity

Commodity	Main model	Maximum price	Minimum price	Fertilizer usage γ_0	Fertilizer usage γ_H
Paddy	0.051***	0.054***	0.049***	0.015	0.063***
	(0.013)	(0.013)	(0.011)	(0.012)	(0.022)
Observations	131,903	129,504	129,532	124,098	—
Groundnut	0.036***	0.048***	−0.028	0.013	0.054**
	(0.014)	(0.010)	(0.031)	(0.016)	(0.021)
Observations	34,944	34,837	34,848	33,542	—
Maize	0.035***	0.024***	0.046***	0.039***	−0.009
	(0.007)	(0.006)	(0.010)	(0.012)	(0.013)
Observations	89,478	87,106	87,105	87,685	—
Cotton	0.015	0.033***	−0.048	0.005	0.020
	(0.012)	(0.010)	(0.045)	(0.015)	(0.023)
Observations	46,055	46,051	46,053	40,813	—
Tur	0.008	0.004	0.017	0.012	−0.007
	(0.016)	(0.015)	(0.020)	(0.021)	(0.031)
Observations	52,953	50,377	50,359	51,283	—
Green Gram	−0.009	−0.006	0.007	−0.013	0.011
	(0.013)	(0.013)	(0.019)	(0.014)	(0.026)
Observations	51,742	50,822	50,836	47,243	—

For all but the "fertilizer usage" model, we report the γ estimates for the implementation dummy ($I_{m,t}$) in Eq. **1**. For the fertilizer usage model, we report the estimates of γ_0 and γ_H in Eq. **2**. Standard errors (in parentheses) are clustered at the market level. In all models, we control for district-level yearly production, yearly yield, monthly rainfall, and state-level per capita GDP, as well as market and week fixed effects. ***, $p < 0.001$; **, $p < 0.05$.

UMP (14).[*] However, the analysis also shows that the implementation of UMP has not generated statistically significant impacts on the modal prices of cotton, tur, or green gram. These results remain valid in a number of robustness analyses (see *SI Appendix, Robustness Tests* for more details).

Heterogeneous Impacts by Product Quality

One natural question is whether farmers who produce higher-quality products benefit more from an online agri-platform such as the UMP.[†] To investigate this question, we perform two additional analyses. First, we examine the impact of UMP on the maximum price and minimum price of the six commodities. Compared to the results on modal prices, we observe an additional impact of UMP on the maximum price of cotton but do not observe a significant impact on the minimum price of groundnut (Table 1, columns 2 and 3).

Second, we use farmers' fertilizer usage per unit of farmland as a proxy for the respective product quality and analyze whether the impact of UMP differs for farmers with high vs. low usage.[‡] To do so, we first identify Karnataka markets located in districts with fertilizer usage above the median usage across all districts in the state. We then estimate the impact of UMP on the modal prices in these markets compared to the remaining markets (Eq. **2**). The estimated differential impact is presented in Table 1, column γ_H. We observe a statistically significant differential impact for paddy and groundnut. Specifically, paddy and groundnut farmers with above-the-median fertilizer usage gain a greater price increase than those with below-the-median fertilizer usage. Note, however, that we do not find differential impact with respect to fertilizer usage for maize, despite a significant overall price increase for this commodity.

Our field interactions with the traders and domain experts, as well as some documented evidence (16, 17), indicate that paddy, groundnut, and cotton are commodities whose prices are sensitive to quality. In contrast, price for maize is less sensitive to its quality as maize is predominantly used as cattle feed in the country (18). We find some evidence in line with these expectations in the UMP data. Specifically, we should expect to see more price variation across lots on a given day for commodities whose price is more sensitive to quality. Indeed, the coefficient of variation (CV) of the prices across lots within any given day and market is substantially higher for paddy, groundnut, and cotton than for maize. The average CV of prices across all days and markets is 0.141, 0.135, and 0.118 for paddy, groundnut, and cotton, versus 0.043 for maize. A regression analysis confirms that the CV of prices for the former three commodities is significantly higher than that for maize. Taken together, the above analyses suggest that the implementation of UMP may have generated greater benefits for farmers who produce higher-quality products. See *SI Appendix, Farmer Heterogeneity* for further details.

The disparate impacts of UMP across different commodities motivate us to investigate what systemic factors potentially contribute to these differences. This investigation is informed by our extensive field visits and interviews with farmers, commission agents, traders, and mandi officials in Karnataka. Hereafter, we refer to paddy, groundnut, and maize as the "high-impact" group (i.e., commodities for which UMP has yielded a statistically significant, positive impact), and we refer to cotton, tur, and green gram as the "low-impact" group (i.e., commodities for which UMP has not generated a significant impact). The analysis suggests four factors that distinguish the high-impact group from the low-impact group: logistical challenges for cross-market trading, the increased efficiency of bidding under UMP, the level of in-market concentration for a commodity, and the price discovery process used. The first three factors relate to how the

[*] The assumption underlying this derivation is that the farmers' costs and production quantities have not changed significantly due to UMP.

[†] Since we do not have data directly on product quality, we rely on multiple sources to understand for which commodities prices are likely to be sensitive to quality. These include our field interactions with the traders and domain experts, academic references, and analyzing within-day price variation across lots in the UMP data.

[‡] The presumption that higher fertilizer usage indicates better overall quality of the commodities grown in the district is based on evidence in the agricultural sciences (15), and it is reasonable in the setting of resource-constrained smallholder farmers where overuse of fertilizers is unlikely.

implementation of UMP may have increased competition among traders (or not), and the last factor relates to increased bargaining power for farmers due to price transparency. We observe mild correlations among these factors, suggesting that they each capture some distinctive aspect of differences between the high-impact and low-impact groups (*SI Appendix, Comparing High-Impact and Low-Impact Groups*).

Systemic Differences between High-Impact and Low-Impact Groups

Cross-Market Competition. Transportation and logistics costs are believed to be significant barriers to effectively integrating agricultural markets in developing countries (7). Our field visits to the mandis reveal that logistical infrastructure is still lacking to support cross-market trading. Specifically, traders are fully responsible for processing and transporting all of the lots they have won within the same day, regardless of where the lots are located. Traders need to hire additional laborers, representatives, and transporters to handle these tasks, adding costs and coordination challenges across mandis. Thus, we postulate that cross-market trades would be more likely to occur for commodities whose major markets are closely located from each other, compared to commodities whose major markets are geographically spread out. Because increasing market competition—in part by enabling cross-market trades—is conceived as a key mechanism to improve prices for farmers, we make the following hypothesis:

H1. The major markets for commodities in the high-impact group are more closely located than those in the low-impact group.

Evidence. To test H1, we compare the pairwise distances among the major markets by quantity between commodities in the high-impact group versus those in the low-impact group. The set of major markets for a commodity is the largest markets where 90% of all quantities are traded. We focus on major markets by quantity because cross-market trading, if any, most likely occurs among markets with large quantities. A t test confirms that the major markets for commodities in the high-impact group (paddy, groundnut, and maize) are indeed closer to each other ($t = -5.495$, $p < 0.0001$). The policy recommendation from this analysis is that the benefits of online agri-platforms can be enhanced by building logistical infrastructure conducive to cross-market trades. Possible options include providing cross-market traders with services of post-trade sorting and processing, arranging third-party logistics providers (with long-term contracts) to facilitate transportation, and providing other similar pooling services that can leverage economies of scale and hence lower the logistics costs associated with cross-market trading for the traders.

In-Market Competition. Our field interviews with traders reveal that a key benefit from UMP to them is the increased efficiency in trading and bidding due to the online platform. In traditional mandis, traders need to visit each commission agent shop to submit their bids or negotiate in a sequential manner. For commodities whose supply is distributed across many commission agents, this process is very time-consuming. As a result, traders often can visit only a limited number of agents within the day, which in turn limits the number of bids each lot receives. In contrast, under UMP, traders can quickly visit many agents to inspect the lots and privately record their bids on a tender slip before submitting all bids online all at once. This increased efficiency could lead to an increase in the number of bids per lot (and hence, the winning price) under UMP. Note that this effect would be stronger for commodities whose supply is more distributed across agents, and hence the efficiency gain would be more prominent. We summarize the above logic in the following hypothesis:

H2. Commodities in the high-impact group have more distributed supply among commission agents than those in the low-impact group.

Evidence. We use the Herfindahl–Hirschman index (HHI) to quantify the level of supply concentration among commission agents for different commodities, denoted as HHI-a (19). In particular, the HHI-a for a commodity in a given market is defined as the sum of squares of each commission agent's supply share of that commodity in the market, where an agent's supply share is the fraction of total market quantity sold at the agent's shop. A larger value of HHI-a implies a higher level of supply concentration among the agents. Fig. 2*A* presents the distribution of the average HHI-a for the high-impact group (green) and the low-impact group (red) across all markets trading these commodities. We confirm with a t test that commodities in the high-impact group (paddy, groundnut, and maize) are associated with a lower HHI-a (i.e., a larger number of agents splitting the total quantity), supporting H2 ($t = -2.981$, $p = 0.003$).[§]

We also utilize the detailed lot-level auction data from the UMP to examine whether the extent of competition in the markets has changed postimplementation. We observe that the average number of bids received by each lot has significantly increased for paddy, groundnut, maize, and cotton; however, it has decreased for tur and green gram (*SI Appendix, Structural Changes in the Markets*).[¶] These results are consistent with the expectation that a larger increase in the level of competition among traders can result in a stronger benefit from UMP. The policy implication is that the benefits of online agri-platforms can be enhanced further by reducing search costs for traders in the markets. For example, pooling lots of similar quality and/or quantity can allow traders to identify prospective lots more efficiently both within and across markets.

In-Market Concentration. A key drawback in traditional mandis that has been extensively reported is the presence of collusion and price manipulation by traders (13). Due to the traditionally manual and undocumented auction process, it was easy for traders to collude among themselves or with commission agents and change bid prices in the tender slips. It is easier for such collusion and price manipulation to occur when market power is concentrated on a small number of traders. One intended benefit of UMP is to deter these collusive behaviors by digitally recording bids, automating winner determination, and disseminating winner information to farmers. Given this logic, we postulate two opposing effects from in-market concentration. First, if market concentration is low, then the extent of collusion prior to UMP's implementation may already be low, and hence UMP would have a small impact for commodities with low market concentration. Conversely, if market power is highly concentrated among a few dominant traders, then there remain risks of these traders forming bidding rings to manipulate prices even under UMP. As a result, UMP would have a limited impact for commodities with high market concentration. We thus propose two competing hypotheses to be examined with the data:

H3a. There is higher concentration of in-market power among traders for commodities in the high-impact group than for those in the low-impact group.

H3b. There is lower concentration of in-market power among traders for commodities in the high-impact group than for those in the low-impact group.

[§]This result is also confirmed by a regression analysis that clusters standard errors at the market level. Similar analyses are done for H3 and H4. See *SI Appendix, Comparing High-Impact and Low-Impact Groups* for more details.

[¶]We do observe a limited extent of cross-market trading (2 to 12% of the traders across commodities) that may correlate with our results on the average number of bids per lot. See *SI Appendix, Cross-Market Trading* for more details.

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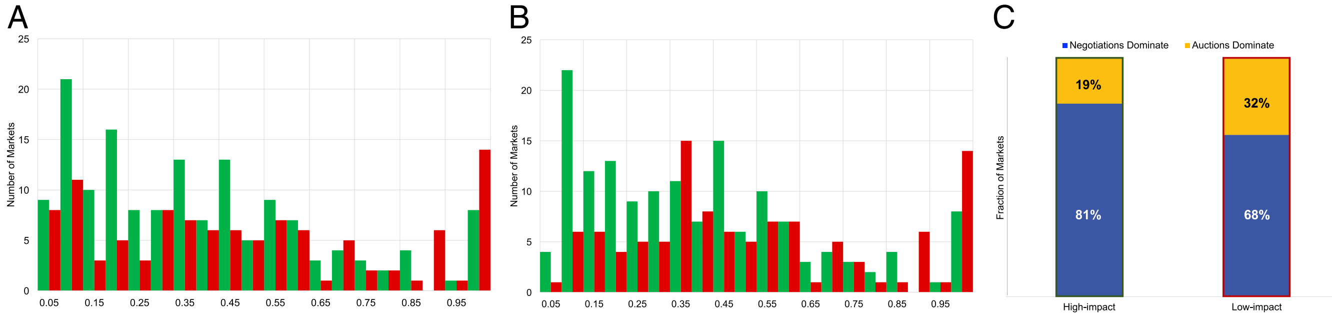

Fig. 2. *A* ($n = 258$) and *B* ($n = 258$) present the distribution of the average HHI-a and average HHI for the high-impact group (green) and the low-impact group (red) across markets. *C* ($n = 461$) presents the fraction of markets in which negotiations (blue) or auctions (yellow) dominate. *Left* bar considers markets for the high-impact group; *Right* bar considers markets for the low-impact group.

Evidence. We again use the HHI to quantify the level of market concentration for different commodities. Specifically, the HHI for a commodity in a given market is defined as the sum of squares of each trader's market share of that commodity in the market. In our context, a trader's market share corresponds to the fraction of total market quantity bought by the trader. A larger value of HHI implies a higher level of market concentration. Fig. 2*B* presents the distribution of the average HHI for the high-impact group (green) and the low-impact group (red) across all markets trading these commodities. A t test shows that commodities in the high-impact group (paddy, groundnut, and maize) are associated with a lower HHI (i.e., a larger number of traders splitting the total quantity; $t = -3.678$, $p = 0.0003$). This result supports H3b instead of H3a. The policy implication is that the benefits of online agri-platforms can be enhanced further by reducing entry barriers to attract new traders or by adopting alternative price discovery mechanisms to intensify within-market competition.

Price Discovery Process. The lack of price transparency in the traditional system wherein farmers had to rely on traders for price information was a key issue negatively affecting market outcomes for farmers. To increase transparency, the government has installed computer kiosks with price information and also started sending price information through SMS messages to farmers. By allowing farmers to access price information in real time, farmers' bargaining power vis-a-vis traders is expected to increase. The effect of such increased bargaining power on final prices would depend on the price discovery process used. With direct negotiation, farmers could potentially use the price information to their advantage and bargain with traders more proactively. In contrast, the scope of bargaining is limited when prices are determined via first-price sealed-bid auctions (without reserve prices). Therefore, we posit that for commodities in the high-impact group, direct negotiation may be used more prevalently than auctions, leading to the following hypothesis:

H4. A larger fraction of quantity is traded through direct negotiations as opposed to auctions for commodities in the high-impact group than for those in the low-impact group.

Evidence. Fig. 2*C* presents the proportion of markets in which a larger fraction of quantity is traded through negotiations (blue) versus auctions (yellow), separating the high-impact group (Fig. 2 *C*, *Left* bar) and the low-impact group (Fig. 2 *C*, *Right* bar). We observe that negotiations are indeed used more frequently for commodities in the high-impact group (paddy, groundnut, and maize). A t test that compares the fraction of quantity traded through negotiations between the high-impact and low-impact groups confirms this observation, supporting H4 ($t = 3.822$, $p = 0.0002$). The policy implication from this result is that online agri-platforms using auctions would benefit farmers more with additional means to increase the bargaining power of farmers. For instance, farmers can be recommended reserve prices for their lots based on prevailing market rates.

Conclusions and Discussion

While online agri-platforms provide the desirable infrastructure to enable potential integration of distant agri-markets, the results from this paper highlight that their success critically depends on systemic supply chain logistics and process design considerations that affect trades in the physical markets. For example, providing integrated logistics can encourage and facilitate cross-market trading, pooling lots of similar quality can further reduce traders' search costs and enhance bidding efficiency, and optimizing the auction design can further increase market competition and strengthen the farmers' bargaining power. These practical insights are relevant and applicable to the design and optimization of other similar agri-platforms beyond the case of UMP. In addition, the results also show that an integrated agri-platform such as the UMP generates greater benefits for farmers who produce high-quality products.

Three limitations in the current study are worth discussing. First, traders do not necessarily submit the cross-market bids themselves, but often use "delegates" in other markets to bid on their behalves. Since cross-market bidding through delegates is not identifiable in the UMP data, we can provide only a lower bound on cross-market trading. Despite this limitation, we find that directional results on cross-market trading are in line with our hypothesis on logistical challenges (*SI Appendix, Cross-Market Trading*). Second, to evaluate H2 to H4, we use the UMP data to measure potential differences in market structure across commodities, assuming that these structural features remain similar before and after UMP's implementation. We have to do so because detailed market structure data are not available for Karnataka markets prior to UMP's implementation. In *SI Appendix, Structural Changes in the Markets*, we discuss mild changes in some of the market features since UMP's implementation. Similarly, data on these market features are not available for the control markets. Hence, we cannot directly analyze the moderating effects of these features on the impact of UMP. Third, we do not have data on product quality and thus rely on the analyses on maximum/minimum price and fertilizer usage to shed light on how the benefit of UMP may vary by product quality. As the government continues to scale its quality assaying efforts, future studies can utilize the resulting data to more directly investigate the role of product quality in affecting the realized benefit of an integrated agri-platform such as the UMP.

Materials and Methods

DID Model. We use a DID approach to estimate the impact of UMP on the prices of various commodities. Note that different markets in Karnataka were integrated into UMP at different, exogenously determined dates (*SI Appendix, Dates of Integration*). All Karnataka markets, once integrated into UMP, are considered as treatment markets. All non-Karnataka markets are considered as control markets. Specifically, we estimate the following model for each commodity separately:

$$\log(P_{m,t}) = \gamma I_{m,t} + \delta \log(Q_{m,t}) + \Theta X_{m,t} + \alpha_m + \beta_t + \epsilon_{m,t}. \quad [1]$$

The dependent variable $\log(P_{m,t})$ is the logarithm of the modal price, maximum price, or minimum price observed in market m at week t. The key independent variable is the implementation dummy: $I_{m,t} = 1$ if market m has been integrated into UMP at week t and 0 otherwise. The variable $Q_{m,t}$ is the total quantity in market m at week t, and $X_{m,t}$ denotes the vector of all control covariates discussed earlier. We control for market fixed effects (α_m) and week fixed effects (β_t). $\epsilon_{m,t}$ is the idiosyncratic error term. The coefficient of interest is γ. A positive and significant value of γ indicates that the implementation of UMP has led to a significant increase in the commodity's modal, maximum, or minimum price.

To analyze potentially heterogeneous impacts of UMP for farmers with different fertilizer usage, we estimate the following model for each commodity:

$$\log(P_{m,t}) = \gamma_0 I_{m,t} + \gamma_H I_{m,t} \times F_m^H + \delta \log(Q_{m,t}) + \Theta X_{m,t} + \alpha_m + \beta_t + \epsilon_{m,t}. \quad [2]$$

The additional variable F_m^H is an indicator variable for high fertilizer usage. That is, $F_m^H = 1$ if the fertilizer usage per unit of farmland in the district where market m is located is above the median of the distribution of fertilizer usage across all districts in the state, and $F_m^H = 0$ otherwise. A positive and statistically significant value of γ_H indicates that farmers in districts with above-the-median fertilizer usage benefit from a larger price increase due to UMP compared to the rest of the farmers.

Robustness Tests. We perform a number of robustness analyses to strengthen our results. In particular, we consider 1) five alternative model specifications, 2) p-value adjustments to account for multiple hypothesis testing, and 3) three alternative specifications with different control covariates. We consider our main result to be robust if the direction and statistical significance of the coefficient for the implementation dummy are consistent between the main model and these robustness tests. We confirm that this is the case for all six commodities (*SI Appendix, Robustness Tests*).

DID Assumption. Following ref. 3, we perform the following parallel trend test for each commodity using the data prior to the first market being integrated on UMP:

$$\log(P_{m,t}) = \gamma_1 t + \gamma_2 I_m^K t + \delta \log(Q_{m,t}) + \Theta X_{m,t} + \alpha_m + \epsilon_{m,t}. \quad [3]$$

The variable t denotes the number of weeks since the start of the data. The dummy variable $I_m^K = 1$ if market m is a Karnataka market and 0 otherwise. The remaining variables follow from Eq. **1**. A nonsignificant γ_2 indicates that we cannot reject the null hypothesis that prices in the treatment and control markets follow the same linear pretrend (*SI Appendix, Parallel Trend Test*).

Falsification Test. We follow ref. 20 to perform a falsification test. In particular, we reestimate model **1** 1,000 times with the data from the pretreatment period and assuming randomly selected placebo dates as the implementation dates each time. We confirm that the empirical distribution of the estimated effects from this falsification test is close to zero and significantly smaller than the estimated impact with the true implementation dates for paddy, groundnut, and maize, and it is not statistically significantly different from zero for cotton, tur, or green gram (*SI Appendix, Falsification Test*).

Data Availability. Data sources 1 and 2 in Data and Empirical Approach were collected from public sources and can be accessed via the following links: http://agmarknet.gov.in, http://www.aps.dac.gov.in, http://www.imd.gov.in, http://www.niti.gov.in, and http://vdsa.icrisat.ac.in. Data source 3 was obtained under a nondisclosure agreement with ReMS and can be obtained at Harvard Dataverse, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/O19FOR. We provide aggregate information and detailed results from the analysis using UMP data in *SI Appendix*.

ACKNOWLEDGMENTS. We are grateful to Jingwen Tang and Ziwei Zhu for their excellent research assistance; to Manik Joshi, Mangala Patil, Nisha Devra, and ReMS staff members for their tremendous support in the field; and to the editor and two anonymous reviewers for their constructive comments on an earlier draft of this paper. We gratefully acknowledge financial support from the Tata Center for Technology and Design at Massachusetts Institute of Technology.

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