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Effects of electronic markets on prices, spikes in prices, and price dispersion: A case study of the tea market in India

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Abstract

Buyers and sellers in developing countries are often restricted from accessing distant markets by asymmetric price information and costly searches. Electronic marketplaces can reduce transaction costs and improve market performance. This study uses monthly panel data from 2000 to 2017 and applies a fixed effects approach using Driscoll and Kraay standard errors to address spatial and temporal correlations to provide empirical evidence on the effects of electronic markets on prices, spikes in prices, and price dispersion of an agro-based commodity in India. The findings indicate that, between 2000 and 2017, the introduction of electronic markets reduced prices and short-term variability in tea prices by nearly 2%. Moreover, electronic markets initially increased price dispersion between markets by 11%–14%; however, with further reduction in market friction over time, price dispersion reduced by 16%. [EconLit Citations: Q11, Q13].

KEYWORDS

agriculture, electronic marketplaces, ICTs, market efficiency, price dispersion

Abbreviations: CD, compact disc; e-NAM, electronic National Agriculture Market; ICT, information communication technology; INR, India rupee; LMIC, low- and middle-income countries; LSDV, least squares dummy variable; MIS, management information system; OLS, ordinary least squares; SMS, short message service.

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1 | INTRODUCTION

Asymmetric price information in agricultural markets results in wide spatiotemporal variation in prices (Abdulai, 2000; Moser et al., 2009). Problems related to information often limit mutually beneficial exchanges in low- and middle-income countries (LMICs) because high search costs prevent buyers and sellers from finding each other or acquiring enough information for confidently making transactions (World Bank Group, 2016). Moreover, high entry costs into local markets help oligopsonists to maintain selling prices below competitive prices (Meenakshi & Banerji, 2005; Rogers & Sexton, 1994; Sexton, 1990; Shimamoto et al., 2015), while at the buyers' end, prices are raised above the marginal cost due to intermediaries' market power (Burdett & Judd, 1983; Salop & Stiglitz, 1977; Stahl, 1989, 1996; Varian, 1980). Thus, high information costs reduce the scope of market exchange and lead to economy-wide Pareto inefficiencies (Greenwald & Stiglitz, 1986; Stiglitz, 1988). In such situations, how to increase agricultural market efficiency is an important policy question in the context of LMICs. Some studies have highlighted that information technology can reduce information asymmetries and increase market efficiency (Aker, 2010; Jensen, 2007), while some have shown mixed empirical evidence on the implications of market information systems (MIS) on farm gate prices (Aker & Fafchamps, 2014; Fafchamps & Minten, 2012; Goyal, 2010; Haile et al., 2019; Mitchell, 2017; Shimamoto et al., 2015; Svensson & Yanagizawa, 2009).

The rise in high-speed Internet connections in recent years has led to increased use of information communication technology (ICTs). Several Internet-based applications and technologies, which could reduce the time and cost of processing and communicating information, are being developed. The rapid adoption of the Internet has led to the emergence of electronic marketplaces that aggregate supply and demand by connecting buyers directly to sellers through a digital platform (Baumüller, 2018; Rao et al., 2017). Economists have suggested that electronic markets can decrease search costs and help both sellers and buyers of homogeneous and differentiated products (Bakos, 1997). However, studies conducted in high-income countries on the effects of online commerce on consumer durables, such as cars, books, compact disks, and term life insurance, have found mixed evidence on the impact of electronic markets on prices and market efficiency. Few studies have reported reduced prices and efficient markets, while others have reported higher prices and probable inefficiency of the electronic markets (Brown & Goolsbee, 2002; Brynjolfsson & Smith, 2000; Clay et al., 2001; Lee et al., 1999, 2003). As empirical studies on the effects of electronic markets on other Internet markets are inconclusive, an in-depth examination of this subject is warranted. Moreover, there is limited empirical evidence in the context of LMICs and commodities with limited shelf life. There is perhaps only one published study that analyses the impact of electronic marketplaces on market prices and farmers' profitability (Levi et al., 2020). This study makes two contributions to this limited literature by empirically analyzing the implications of electronic markets on market performance through a case study of the tea sector in India. First, we examine the relationship between the introduction of electronic markets and auction prices, spikes in tea prices, and price dispersion between markets in an LMIC using data from six tea auction centers in India from 2000 to 2017. Second, we investigate the effect of an electronic market on an agricultural product with limited shelf life.

This study is presented as follows: In Section 2, we discuss India's tea market and the mechanism of introducing electronic markets. In Sections 3 and 4, we discuss the conceptual framework and the materials and methods used in the study, respectively. We present the descriptive analysis and econometrics results in Section 5 and the conclusion in Section 6.

2 | TEA MARKET IN INDIA

2.1 | Overview of the tea market in India¹

In India, the production and processing of tea play a key role in employment, rural food security, and foreign exchange earnings. This sector employs nearly one million people, with women comprising nearly 60% of the workforce. Although Assam is the largest tea-growing region in India, with 53% of total production (Tea Board of India, 2017b), it is also one of the poorest regions, with nearly 40% of the rural population living below the poverty line (Government of India, 2012) and about 50% of daily wage labor employed in the tea industry. India is the second-largest tea producer after China, supplying nearly 23% of global tea production, and contributing about 14% of total exports, thus making India the fourth-largest exporter of tea after Kenya, China, and Sri Lanka. Although tea is an important export commodity generating 0.2% of the total export earnings, India is also one of the largest consumers of tea. Approximately 80% of the tea produced is consumed locally (Tea Board of India, 2017a). Additionally, the deep involvement of smallholder farmers in tea production indicates its significance to poverty alleviation.

The tea value chain has several market participants, from producing green tea leaves and processing bulk tea to selling processed tea to commercial buyers (Figure 1). In the upstream segment, producers of green tea leaves are either small tea growers (less than 10 hectares of land) or large organized plantation estates.² The mid-stream segment includes processors who manufacture bulk tea from green leaves. These processors could be stand-alone processing units or factories belonging to plantation estates. In the downstream segment, processed tea is sold through auctioneers to buyers in the domestic or global market. These buyers either sell the loose processed tea to other agents/retailers or add value by blending and then selling branded tea to consumers. In the tea value chain, the auctioneer is a third-party intermediary who finds buyers and sells the product on behalf of processors through private sales or public auctions by levying a service charge of 1% of the total value of the transaction. The auctioneer also provides services such as cataloging tea, inspecting the quality of tea by tea tasting, providing valuation, and sending samples to buyers located across the country. They charge the buyers a fee of 0.18% of the value of the transaction³ for their services.

Tea can be sold mainly through two marketing channels: private sale of bulk processed tea at negotiated prices and competitive sale of tea through public auctions in designated market areas. In India, tea has been marketed and distributed mainly through public tea auctions since 1861 (Tea e-Auction, 2012). Currently, approximately 47% of the total tea produced in India is sold via auctions through six auction centers that sell only tea and are open to any tea manufacturer registered with the Tea Board of India. Figure A1 in the Supporting Information: Appendix shows the locations of the six auction centers in India. Most of the remaining tea is sold to buyers at negotiated prices, and only a small amount is offered through three smaller auction houses. Of which, two are open exclusively to a select set of growers who cultivate a certain variety of tea and belong to a particular society.

Weekly auctions begin with the transportation of bulk tea from processing units to registered warehouses for sale through the appointed auctioneer. The warehouse keeper creates an arrival and weight report with details showing the date of arrival and any damage or shortfall in arrivals. The auctioneer then catalogs, samples, and evaluates the tea before sending samples to buyers located in different regions. These samples are sent a week ahead of each auction sale, thus allowing buyers to form their valuation and receive orders in time for the next sale. On the day of the auction, registered buyers and auctioneers meet physically at designated centers to competitively

¹Information in this section is based on key informant interviews with officials at the Tea Board of India, United Planters' Association of Southern India, J. Thomas and Co. Pvt Ltd., Tocklai Tea Research Institute, and local tea experts in India.

²According to the Tea Board of India, nearly 44% of the total tea produced in India is grown by small tea growers.

³These rates were fixed by the Tea Board of India. In comparison to the Indian rates, auctioneers in the Mombassa auction center charge the producers 1% and the buyers 0.5%.

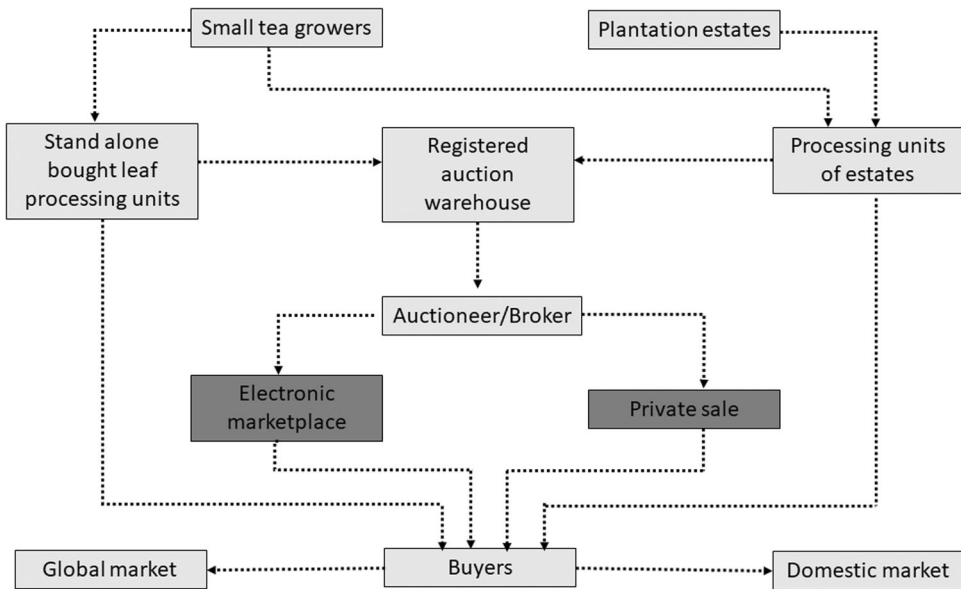


FIGURE 1 Tea value chain in India.

bid for tea till a fair price is reached. Public auctions are usually preferred over private sales as auctions facilitate quick transactions of large quantities of tea and help buyers to purchase wider varieties of tea and sellers access several domestic and external markets. Auction prices also serve as a benchmark for private sales and prices paid for green tea leaves purchased from small tea growers.

2.2 | Introduction of electronic marketplaces

Between 1861 and 2009, weekly physical auctions were conducted through open-outcry ascending prices or English auctions (Tea e-Auction, 2012). In the tea auction system, sellers are brokers or auctioneers who sell processed tea on behalf of tea processors, whereas buyers are traders, retailers in the domestic market, or exporters. There were several market inefficiencies in the earlier public auction system. First, big buyers often colluded and engaged in bid rigging to arrive at lower prices of bulk tea and transferred profits within the value chain to its retail end. Second, buyer representatives had to be physically present in specific markets at different auction centers across India on auction dates, which increased the cost of doing business and, therefore, limited the number of buyers in the tea markets. Third, the existing entry barriers to new markets (such as geographical distance and administrative cost of having agents in different markets) substantially increased the search costs and limited mutually beneficial trade for both buyers and sellers. Thus, between 2009 and 2010, physical auctions were replaced by electronic markets in tea auction centers across India to improve market efficiency. This shift aimed to increase buyer participation, reduce transaction costs, and increase sales volumes. Additionally, the introduction of electronic auctions with anonymous bidding aimed to reduce the chances of buyer collusion.

A downloadable application compatible with desktops and laptops was used to introduce the electronic marketplace in the tea sector functions. It was first introduced in tea-growing regions of southern India, followed by those in eastern India. In May 2009, Coonoor and Coimbatore auction centers introduced electronic marketplaces, followed by Kochi in July 2009. Electronic markets were first introduced in southern India because a pilot electronic marketplace had already been used since 2003 by a group of cooperative factories in Tamil Nadu for Nilgiri tea, a

specific type of tea. In the eastern region, the Guwahati Center introduced an electronic marketplace in January 2010, then Kolkata in April 2010, and Siliguri in October 2010. By October 2011, all auction centers had electronic marketplaces. The transaction rules were identical to that of the physical auction, except that transactions were conducted electronically within each market. Similar to the earlier format, anyone could register with the Tea Board of India and participate in the auction process. Thus, we could study the relationship between the introduction of the electronic marketplace and the tea market performance.

We also highlight that when electronic markets were initially introduced, buyers were still required to register separately for each center to participate in multiple markets; that is, a buyer registered in the Guwahati auction center could transact in another auction center only with a separate registration. The rules for intermarket electronic trading were modified in June 2016 to allow market participants registered in any of the six centers to conduct transactions across all markets with a single registration. This modification of the trading rules, known as the "Pan-Indian electronic auction," aimed to decrease buyers' transaction costs and enhance price discovery through the digitized platform. Key informant interviews with tea experts have indicated that the introduction of the Pan-Indian electronic auction may have played a larger role than the initial introduction of electronic markets. Therefore, we also studied the effects of electronic markets on price dispersion when market friction was further reduced over time by Pan-Indian auctions. In the new system of Pan-Indian electronic auction, tea sellers remained localized and could only bid tea lots at the auction center where they were registered, while buyers could bid at any center without being locally registered. In Figure A2 in the Supporting Information: Appendix, we show the number of buyers and sellers before and after introducing the electronic marketplace at the Guwahati tea auction center, the largest tea auction center in India, which accounts for nearly 31.5% of the total market arrivals. This clearly shows that after the introduction of the Pan-India electronic auction, the number of buyers and sellers at this center has increased.

3 | CONCEPTUAL FRAMEWORK

Theoretically, electronic marketplaces that connect buyers and sellers directly through a digital interface are expected to reduce search costs (Bakos, 1997). Reduction in search costs can ease the amount of search conducted by buyers, which in turn increases price competition among sellers. This is expected to increase market efficiency by reducing price dispersion. In an efficient market, where information about product prices is well disseminated, sellers' prices are expected to converge at a single price such that any seller who charges significantly above the marginal cost will lose buyers (Lee et al., 2003). Thus, from a buyer's perspective, reducing the search costs of retrieving information about seller prices and product offerings through a digital interface allows buyers to source products at lower prices and make more informed bids.

While electronic marketplaces are theoretically expected to increase competition among sellers and reduce market prices, the existing empirical literature on the effects of e-commerce suggests that market prices may not always decrease. Online trade can lead to higher prices when sellers can differentiate their products and offer higher-quality items through the digital platform (Lee et al., 1999) or can reduce buyer collusion through anonymous bidding or attract new buyers, thereby increasing product demand. Figure 2 provides a diagrammatic representation of the various mechanisms through which electronic markets can affect market prices.

The existing empirical evidence also emphasizes that markets need not always become efficient. Price dispersion across markets may increase when Internet markets are newly established and immature (Lee et al., 2003), when Internet markets allow sellers to differentiate their products based on quality and trust (Brynjolfsson & Smith, 2000) or when market agents are heterogeneous in terms of their search costs (Brown & Goolsbee, 2002). From a seller's perspective, the introduction of new technology could initially lead to uncertainties in price setting and adjustments at the margin of prices over quality. Further, from a buyers' perspective, earlier literature on the effects of search costs on equilibrium price distribution has indicated that buyers are

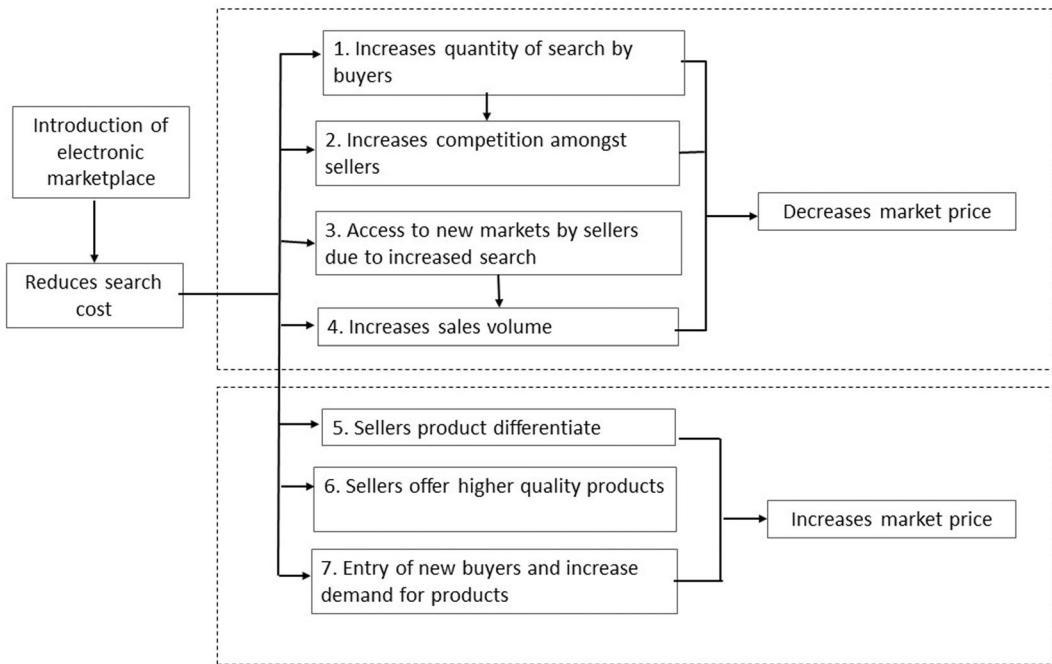


FIGURE 2 Conceptual framework.

heterogeneous in terms of search costs so that a few buyers have no search cost and the rest have a positive search cost (Stahl, 1989). Thus, buyers with positive search costs stop searching when they find a price below their reservation price, while buyers with zero search costs receive price quotes from all sellers and then buy from the cheapest seller (Brown & Goolsbee, 2002; Stahl, 1989). Thus, as the number of uninformed buyers increases, market prices converge to the monopoly price and when the number of fully informed buyers increases, there is increased competition among the sellers and the prices converge to the competitive price.

During physical tea auctions, each lot of tea was sold sequentially, however, when transactions were made electronically, multiple lots were sold simultaneously in each period. As many concurrent auctions for similar grades of tea were conducted electronically, a few buyers with no experience with electronic transactions or low digital literacy may incur higher search costs in the form of time, effort, and analytical ability required to identify the set of potential auctions. Consequently, buyers with high search costs may have conducted narrow searches and identified only a subset of the available auctions. While experienced buyers with low search costs could conduct comprehensive searches and identify all available auctions. Thus, the price dispersion between markets may have increased initially because unaware buyers bid up the prices of some auctions over others (Backus et al., 2014). However, the proportion of uninformed buyers might have decreased over time as markets developed and gained more experience with digital technology, as well as with the advent of the Pan-India electronic auction, which further reduced search costs for buyers.

Furthermore, market agents set their reservation prices based on expected prices. Expectations are formed based on the latest observed prices or by revising expectations based on past errors (Haile et al., 2019). The high cost of acquiring and processing information often leads to uncertainties about the true price levels, leading to forecasting errors and price volatility. Short-term price fluctuations may signal risks and lead to investment uncertainties for all market participants. This could discourage investors and thereby have a negative impact on resource allocation (Kalkuhl et al., 2016). Electronic markets, such as those introduced in the tea sector in India, provide information about the last sold prices of different grades of tea and current prices. Thus, increased access

to information via an electronic platform can enhance market agents' price forecasts and thus reduce the period-to-period spikes in prices.

Thus, our empirical analysis might yield the following results: (1) reduced search costs will reduce transaction costs and prices due to increased competition; (2) with asymmetric search costs between buyers and sellers, as in the case of the Indian tea market, price dispersion will be in equilibrium; (3) in the context of LMICs with low digital literacy, the initial differences in buyers' and sellers' ability to adopt new digital technologies are likely to first increase search costs, and then decrease as markets mature and market agents gain experience. Thus, we expect price dispersion to initially increase and then decrease over time; and (4) better access to information would reduce short-term variability or spikes in tea prices.

4 | MATERIALS AND METHODS

4.1 | Data and study area

This study uses a unique dataset created by compiling secondary data from several sources. Monthly data on auction prices, market arrivals, tea production, rainfall in tea-growing regions, diesel prices, and international auction prices of tea were collected from 2000 to 2017. Indian tea auction prices and market arrival data were compiled from the annual tea statistics market report published by J. Thomas and Co. Pvt Ltd. India has nine tea auction centers: four in the eastern tea-growing region (Guwahati, Kolkata, Siliguri, and Jalpaiguri), four in the southern region (Kochi, Coonoor, Coimbatore, and TeaServe), and one in north India (Amritsar). Of these nine auction centers, the study collects data from active centers. Therefore, this study focuses on a sample of six tea auction centers: Guwahati, Kolkata, Siliguri, Kochi, Coonoor, and Coimbatore. Data for the Jalpaiguri auction center were unavailable because of a lack of sales on most auction days.⁴ Furthermore, the TeaServe auction center markets tea for a group of cooperative tea factories, while the Amritsar auction center markets a small volume of tea produced by the Kangra Tea Planters Society. Data from the latter two are not included in the study because these centers are accessible only to a group of private producers who grow a specific type of tea in a particular region. Rainfall and tea production data were collected from the United Planters' Association of Southern India and Tocklai Tea Research Institute, while the auction prices in international markets were compiled from World Bank commodity price data. Data on diesel prices were collected from Petroleum Planning and Analysis Cell and Indian Oil Corporation Limited.

4.2 | Empirical strategy

To estimate the relationship between electronic markets and tea prices, the following regression model for panel data with fixed effects is used:

$$p_{it} = \beta_1 E_{i,t} + \beta_2 X_{i,t} + \beta_3 S_t + \beta_4 T_t + \alpha_i + \mu_{i,t}, \quad (1)$$

where t is the month from 2000 to 2017, and i is the auction center taking values between 1 and 6. p_{it} is the log of the price of tea at month t , and $E_{i,t}$ is a binary variable equal to one in month t if an auction center introduced an electronic market. $X_{i,t}$ is a vector of time-variant contextual variables that affect the tea prices, such as auction arrivals, world tea prices, domestic diesel prices, and rainfall. Table A1 in the Supporting Information: Appendix contains details on the measurement of variables. S_t is a vector of month dummies to control for the seasonality of

⁴The Jalpaiguri auction center is in West Bengal, where the Kolkata auction center is also located. The Kolkata auction center, which started functioning in the 1970s, is much older than the Jalpaiguri center (started in 2005), and most of the tea produced in West Bengal is sold through the Kolkata auction center.

tea production; α_i is the auction center fixed effect to control for all unobserved time-invariant differences between markets, such as geographical location and market size; and T_t is the time trend. Auction center-specific time trends are also included in certain specifications. The auction centers in the north and south of India might have different seasonal patterns; therefore, we interact the monthly dummies with a region dummy. $\mu_{i,t}$ is a random error term with zero conditional means. Furthermore, to estimate the relationship between electronic markets and short-term price movement, the following equation is derived:

$$\Delta p_{it} = \beta_1 E_{i,t} + \beta_2 V_{i,t} + \beta_3 S_t + \beta_4 T_t + \gamma_i + \mu_{i,t}, \quad (2)$$

where $\Delta p_{it} = \log(P_t) - \log(P_{t-1})$ and (P_t) is the price of tea in period t . Δp_{it} measures the month-to-month change in prices, which is used as an indicator for sudden spikes in tea prices. Studies on food price volatility have defined a price spike as a large, quick, and transient surge or fall in price owing to short-term shocks (Kalkuhl et al., 2016; Tadesse et al., 2014). In the context of the tea sector, short-term variability in prices should be analyzed because sudden spikes in prices lead to uncertainties that could disincentivize investment and optimal resource allocation for all market agents. Short-term price spikes enable us to capture price movement due to transitory reasons that are often obscured when using annual price changes. $V_{i,t}$ is a vector of time-variant contextual variables that affect month-over-month price changes of tea, such as spikes in production (or supply shocks), a spike in diesel prices, average rainfall in tea-growing regions, and world tea prices. Other variables are similar to the earlier specification, and the details of the measurement of variables are presented in Table A1 in the Supporting Information: Appendix.

Furthermore, following the empirical method used by Aker (2010) and Andersson et al. (2017), market efficiency in terms of spatial price dispersion between markets is measured by comparing the price dispersion between pairs of auction centers where both centers have access to electronic markets at a given time and comparing the price between pairs of centers where at least one center lacks access to electronic markets. The absolute price dispersion between markets is expected to reduce when markets become more efficient. Thus, to analyze the association between electronic markets and market efficiency, the following model is estimated:

$$|p_{jt} - p_{kt}| = \gamma_1 E_{jk,t} + \gamma_2 Z_{jk,t} + \gamma_3 S_t + \gamma_5 T_t + \theta_{jk} + \varepsilon_{jk,t}, \quad (3)$$

where $|p_{jt} - p_{kt}|$ is the log of absolute price dispersion of prices in auction centers j and k at time t . $E_{jk,t}$ is a dummy variable equal to 1 if both auction centers j and k have an electronic marketplace in time t ; otherwise, 0. $Z_{jk,t}$ is a vector of time-variant contextual variables affecting price dispersion between two auction centers, such as absolute arrival dispersion, the average rainfall in the tea-growing region where the markets are located, world prices of tea, and a spike in diesel prices. Furthermore, θ_{jk} are market-pair fixed effects to control for all unobserved time-invariant differences between market pairs and $\varepsilon_{jk,t}$ is a random error term. Moreover, to control for market performance at $t - 1$ affecting market performance at period t , a lagged variable of the dependent variable is also included in an alternative specification of Equation (3).

Additionally, we analyze the effects of the introduction of the Pan-India electronic auction on price dispersion by estimating Equation (4). Here the specification is the same as that in Equation (3), except for the inclusion of an additional dummy variable $I_{jk,t}$, which takes a value of 1 for all periods from June 2016 when the rules of electronic trading were made flexible to further reduce search costs and improve price discovery through the digitized platform. Thus, to understand the effects of Pan-India electronic auctions, we are interested in the coefficient γ_2 .

$$|p_{jt} - p_{kt}| = \theta + \gamma_1 E_{jk,t} + \gamma_2 I_{jk,t} + \gamma_3 Z_{jk,t} + \gamma_4 S_t + \gamma_5 T_t + \theta_{jk} + \varepsilon_{jk,t}. \quad (4)$$

In this study, given that the number of cross sections (N) is small, and the time dimension (T) is large, the within-estimator is computed using least-squares dummy variable (LSDV) estimation. Equations (1-4) are estimated using OLS regression of the outcome variables on the contextual variables as specified and N individual dummy variables

representing the number of auction centers (or market pairs), which yields the within estimator for β and γ along with estimates of the N fixed effects (Cameron & Trivedi, 2005).

There are several concerns to consider when using long panel data. First, the validity of the results depends on whether the variables used in the model are stationary. Time series variables often show spurious associations with another series simply because of the presence of a trend component. A time series variable is stationary when its mean and variance are independent of time. Thus, to check for stationarity, we perform three types of panel unit tests, excluding structural change: Fisher type, Levin-Lin-Chu, and Harris-Tzavalis. These results are presented in Tables A2 and A3 in the Supporting Information: Appendix. Additionally, in long panels, there are often concerns about structural breaks that could affect the behavior of unit root tests. Therefore, using the Karavias and Tzavalis (2014) approach, we also show the panel data unit root tests accounting for structural breaks in the intercepts of the individual series and the linear trends in Table A4 in the Supporting Information: Appendix. All tests indicate that we reject the null hypothesis of a unit root at the 1% level of significance for the transformed variables used in our analysis. Therefore, we treat all-time series variables as stationary.

Second, heteroscedasticity, contemporaneous or spatial correlation, and autocorrelation are common problems with cross-sectional time series data. In this study, auction centers located in different regions are likely to experience observable and unobservable common disturbances that could eventually lead to correlations between the residuals from different cross-sections. If the unobservable common factors are not correlated with the control variables, then the coefficient estimates using the standard fixed effects estimator are consistent but inefficient. However, standard error estimates of frequently used covariance matrix estimation techniques, such as OLS, White, and Rogers or clustered standard errors, are biased; therefore, statistical inference based on such standard errors is invalid (Hoechle, 2007). To ensure the validity of the statistical results, Driscoll and Kraay standard errors for coefficients are also estimated with fixed effects (within) regression. The standard errors are robust to spatial and temporal dependence when the time dimension becomes large. Furthermore, this nonparametric technique of estimating standard errors does not restrict the number of panels; thus, it is a suitable method of estimation in the case of a small panel and large time dimensions (Driscoll & Kraay, 1998; Hoechle, 2007). The fixed effects estimator is implemented in two steps. In the first step, all variables are within the transformed regression model, and the second step estimates the transformed regression model by pooled OLS estimation with Driscoll and Kraay standard errors (Hoechle, 2007).

Third, the market performance at time t is expected to depend on that during the previous period. Therefore, the dependent variable lagged in time is also included as a control in different specifications of Equation (1). The LSDV estimator with a lagged dependent variable as a regressor is known to be biased and inconsistent when the time dimension of the panel (T) is small (Kiviet, 1995, 1999; Nickell, 1981). The LSDV estimator is asymptotically valid only when the time dimension of the panel is large (Baltagi, 2005; Kiviet, 1995). In this study, given that the time dimension is large ($T = 216$) compared with the number of cross-sectional units ($N = 6$), the bias is negligible. Moreover, the bias can be more severe for the coefficient of the lagged dependent variable (Judson & Owen, 1999) than for the coefficient of the dummy variable representing the introduction of the electronic marketplace, which is the focus of this study.

Fourth, as mentioned earlier, long-time series data are often subject to structural breaks due to changes in government policies or domestic and international shocks, which can adversely affect estimation and inference (Ditzen et al., 2021). The introduction of electronic trading itself represents a structural break in the time series and is treated as such in the regression model. Therefore, no additional structural breaks are considered in our main regression model. However, we test for structural breaks for the six auction centers using the Supremum Wald test at an unknown break date. The observed dates for structural breaks are presented in Table A5 in the Supporting Information: Appendix. In five of the six markets, the detected structural break occurred during the 2008 financial crisis. We test the consistency of our results with respect to the inclusion of the structural break in a separate robustness check. We use the estimated break dates as an additional dummy variable in Equations (1) and (2) to examine whether the results are robust to structural breaks. We discuss this further in Section 5.

5 | RESULTS AND DISCUSSION

5.1 | Descriptive analysis

Panel A in Table 1 presents the summary statistics of the market-level data, which show a statistically significant difference in average auction prices before and after the introduction of electronic markets; however, there is no significant difference in month-on-month changes in the tea prices. Without controlling for any other factors, Table 1 highlights that the average prices of tea in real terms marginally increased from INR 100.24/kg to nearly INR 103.86/kg after the introduction of electronic marketplaces. Similarly, significant differences in market arrivals, prices of diesel, and world tea prices were found in the preintervention period than in the postintervention period. However, there is no statistically significant difference in the average rainfall in the tea-growing regions between the two periods. Further, Panel B presents the summary statistics for the market-pair data. The data indicate that without controlling for other covariates, the unconditional average price dispersion between markets significantly increased by INR 3.78/kg after the introduction of the electronic marketplace than that before the introduction. Similarly, the average differences of the other covariates used in Equation (3), such as dispersion in market arrivals and world tea prices, also show statistical significance. These differences in the average tea prices and the price dispersion between markets are unconditional means without considering other factors that might affect market performance.

Figure 2 presents the monthly prices of tea in real terms in each auction center between 2000 and 2017, and Figure A3 in the Supporting Information: Appendix plots spikes in tea prices. Figure 2 shows considerable variations in tea prices in all markets in India, which can also be observed in the graphs plotting the month-on-month change in tea prices in Figure A2 in the Supporting Information: Appendix. Further, we plot the absolute price dispersion between market pairs in Figure A4, which also shows substantial volatility before and after the introduction of an electronic marketplace (Figure 3).

5.2 | Association between electronic markets and tea prices

In this section, we analyze the relationship between electronic markets and prices and spikes in tea prices. In Table 2, we present seven fixed effects specifications of Equation (1) with price levels as our outcome variable. Without controlling for any other factors that affect tea prices, column (1) shows that prices are positively and significantly affected by electronic marketplaces. However, once we control for other factors, the sign of the coefficient of electronic marketplaces is reversed (columns 2–7). In column (2), contextual variables such as tea arrivals at auction markets, world tea prices, a spike in diesel prices, and the average rainfall in tea-growing regions are included along with other variables to control for seasonality, common time trends, market-specific time trends, and market-fixed effects. Column (2) shows that electronic markets reduced the tea auction prices by 4.4%. In column (3), we add the lagged dependent variable to allow for market performance at time t to depend on the previous period's performance. Adding lagged prices as a covariate to the specification of Equation (1) reduces the effect of electronic marketplaces to 2.6%; however, the effect is still negative and statistically significant at the 1% level. The inclusion of the lagged dependent variable in Equation (1) helps to distinguish between the short- and long-run adjustments. However, owing to a possible inconsistency of the LSDV estimator concerning the lagged dependent variable, we avoid interpreting the long-run adjustment. Further, to adjust the estimates for the spatiotemporal dependence, the standard errors are clustered by quarters in column (4) and by markets in column (5), respectively. In columns (6) and (7), the main model is presented with Driscoll and Kraay standard errors, which address heteroscedasticity, autocorrelation, and contemporary correlation. The results are still negative and statistically significant. As an additional robustness check for a structural break in the relationship between the variables, we re-estimate Equation (1) by including a binary variable that takes a value of 1 for all periods after the

TABLE 1 Summary statistics.

	Before the introduction of electronic markets			After the introduction of electronic markets				
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
<i>Panel A: Market-level data</i>								
Nominal auction prices (Rs/kg)	62.73	21.01	28.98	142.43	108.99***	31.54	51.30	195.57
Real auction prices (Rs/kg)	100.24	28.08	46.77	205.28	103.86**	27.59	54.49	171.15
Spike in real auction prices (%)	0.00	0.10	-0.33	0.43	0.00	0.10	-0.25	0.57
Auction arrivals (tonnes)	6866.37	4828.25	393.00	23,553	7652.14***	6103.34	468.00	27,834
Nominal diesel prices (Rs/L)	26.85	7.34	15.10	40.52	50.32***	8.36	15.10	63.24
Real diesel prices (Rs/L)	41.72	6.8	27.63	52.58	47.80***	3.84	30.01	54.82
Nominal world tea prices (USD/kg)	1.9	0.43	1.43	3.37	2.96***	0.25	1.85	3.56
World tea price (index)	63.55	14.36	47.92	112.54	98.99***	8.32	61.95	118.98
Rainfall (mm)	218.99	220.57	0.00	1356.68	227.15	231.44	0.00	1249.43
Real auction prices (log)	4.57	0.27	3.85	5.32	4.61**	0.27	4.00	5.14
Spike in diesel prices (%)	-0.00	0.05	-0.57	0.17	0.00	0.04	-0.57	0.25
World tea price index (log)	4.13	0.21	3.87	4.72	4.59***	0.08	4.13	4.78
Rainfall (log)	4.54	1.74	-2.59	7.21	4.58	1.68	-1.80	7.13
Observations	709				587			
<i>Panel B: Market-pair level data</i>								
Absolute price dispersion between markets (Rs/kg)	28.82	21.60	0.00	129.87	32.60***	25.02	0.11	111.67
Absolute arrival dispersion between markets (tonnes)	5265.85	4363.89	11.00	21,669.90	6755.33***	5587.44	0.57	26,237.94
Average rainfall in tea growing region of market <i>j</i> and <i>k</i> (mm)	221.06	207.23	0.00	1111.67	223.39	209.89	0.00	1079.18
Spike in diesel prices (%)	0.00	0.03	-0.08	0.17	0.00	0.03	-0.10	0.25
World tea price (index)	64.59	15.42	47.92	112.54	99.03***	8.21	83.89	118.98

(Continues)

TABLE 1 (Continued)

	Before the introduction of electronic markets			After the introduction of electronic markets				
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
Absolute price dispersion between markets (log)	2.97	1.06	-4.17	4.87	3.05**	1.14	-2.18	4.72
Absolute arrivals dispersion between markets (log)	8.11	1.13	2.40	9.98	8.35***	1.17	-0.56	10.17
Average rainfall in tea growing regions of market j and k (log)	4.69	1.50	-2.59	7.01	4.71	1.47	-1.80	6.98
World tea price index (log)	4.14	0.22	3.87	4.72	4.59***	0.08	4.43	4.78
Observations	2437				1883			

Note: Mean difference before and after the introduction of electronic marketplaces.

Diesel prices and domestic auction prices deflated by the wholesale price index at 2012 prices.

World tea price index was created by taking average auction prices in Mombasa and Colombo auctions and deflating prices by 2012 prices.

*Significant at 10% level, **significant at 5% level, and ***significant at 1% level.

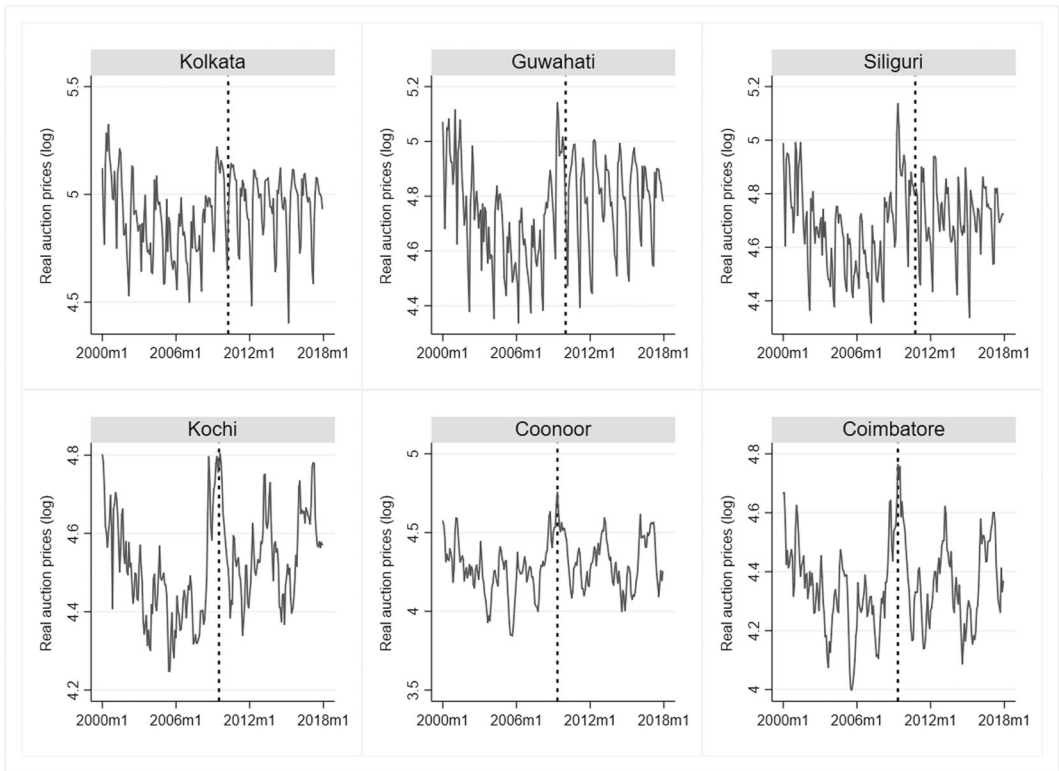


FIGURE 3 Prices of tea in different markets in India.

estimated break. In column (1) of Table A6 in the Supporting Information: Appendix, we show the results for price levels. Even after accounting for the estimated structural breaks, we find a significant and negative association between electronic markets and tea prices. Further, the point estimate of the electronic auction dummy does not differ from those presented in column (7) of Table 2. Therefore, we conclude that the estimates are robust to different specifications with and without lagged dependent variables and after addressing the spatiotemporal dependence and the inclusion of structural breaks using the most conservative estimate, Table 2 suggests that the introduction of an electronic marketplace reduced tea auction prices by about 2.1% than when physical open-outcry auction transactions were prevalent. These results are consistent with the consumer search theory, which predicts that the reduction in search cost increases competition among sellers, and the overall prices of commodities fall in equilibrium, thus increasing the buyers' welfare. The overall effect on producer surplus depends on the effect of electronic marketplaces on the overall sale volumes. As we do not have the monthly data on auction sales, we cannot comment on the overall benefits of electronic markets on sellers.

Additionally, the control variables used in the analysis indicate a significant and negative relationship between domestic auction prices and arrivals of tea and a positive association between auction prices and world tea prices. Indeed, there could be a reverse causality between the auction prices and the auction arrivals, which would bias the point estimate; therefore, as a robustness check, we also present the results of Equation (1) without auction arrivals as a control variable in Table A7 in the Supporting Information: Appendix. The stability of the coefficient estimate of the electronic auction dummy indicates the consistency of its estimation. The coefficient of the variable rainfall shows a negative association with auction prices, because tea withering, which is an important part of the tea manufacturing procedure, depends on the level of atmospheric humidity. When humidity increases, the withering process is altered, which, subsequently, affects the quality of tea and its price. Additionally, the coefficient of the

TABLE 2 Effects of electronic markets on price levels.

	Dependent variable [$\log(P_{i,t})$]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Electronic auction (dummy)	0.038** (0.015)	-0.044*** (0.016)	-0.026*** (0.009)	-0.026* (0.013)	-0.026* (0.010)	-0.026** (0.013)	-0.021* (0.012)
Auction arrivals (log)		0.023** (0.012)	-0.070*** (0.008)	-0.070*** (0.011)	-0.070*** (0.013)	-0.070*** (0.009)	-0.052*** (0.008)
World tea price index ^a (log)		0.209*** (0.027)	0.079*** (0.016)	0.079*** (0.022)	0.079*** (0.008)	0.079*** (0.023)	0.069*** (0.022)
Rainfall (log)		-0.005 (0.005)	-0.005** (0.003)	-0.005* (0.003)	-0.005** (0.002)	-0.005* (0.003)	-0.003 (0.003)
Lagged rainfall ($t - 1$) (log)		0.006 (0.005)	0.002 (0.003)	0.002 (0.004)	0.002 (0.003)	0.002 (0.004)	-0.005 (0.003)
Spike in diesel price		0.304** (0.140)	0.180* (0.101)	0.180 (0.173)	0.180** (0.049)	0.180 (0.175)	0.175 (0.172)
Lagged auction prices ($t - 1$) (log)			0.841*** (0.018)	0.841*** (0.025)	0.841*** (0.027)	0.841*** (0.020)	0.851*** (0.019)
Monthly time dummy	No	Yes	Yes	Yes	Yes	Yes	Yes
Common time trend	No	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	No	Yes	Yes	Yes	Yes	Yes	Yes
Market fixed effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Region \times monthly time dummy	No	No	No	No	No	No	Yes
Observations	1296	1262	1262	1262	1262	1262	1262
R^{2b}	0.005	0.722	0.911	0.911	0.911	0.728	0.837

Note: $P_{i,t}$ is the auction prices of tea in period t in auction center i . Robust standard errors in parentheses (columns 1–5). In column (4), standard errors are clustered by quarters to correct for temporal dependence and in column (5), it is clustered by auction centers to correct for spatial dependence. In column (6), Driscoll and Kraay standard errors are presented in parentheses to correct for heteroscedasticity, autocorrelation, and contemporary correlation. Diesel prices and domestic auction prices deflated by the wholesale price index at 2012 prices.

^a World tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices.

^b Columns (6) and (7) presents within R^2 .

*Significant at 10% level, **significant at 5% level, and ***significant at 1% level.

lagged auction prices suggests that the tea prices in period $t - 1$ have a significant and positive effect on the tea prices in period t .

In Table 3, we present several fixed effect specifications of Equation (2) with month-on-month changes in the prices of tea as the outcome variable. Without controlling for other factors, column (1) shows that the electronic marketplace does not have a significant effect on our outcome variable; however, on the inclusion of other control variables, such as a spike in the production of tea (or supply shocks), world tea prices, a spike in diesel prices and the average rainfall in tea-growing regions, along with variables to control for seasonality, common time trend, market-specific time trends, market-fixed effects and interaction between region and

TABLE 3 Effects of electronic markets on spikes in tea prices.

	Dependent variable [$\log(P_{i,t}) - \log(P_{i,t-1})$]					
	(1)	(2)	(3)	(4)	(5)	(6)
Electronic auction (dummy)	-0.001 (0.006)	-0.024** (0.009)	-0.024* (0.012)	-0.024*** (0.006)	-0.024** (0.011)	-0.024** (0.011)
Spike in production of tea (%)		0.013*** (0.004)	0.013*** (0.004)	0.013* (0.006)	0.013*** (0.005)	-0.003 (0.005)
World tea price index ^a (log)		0.049*** (0.016)	0.049** (0.022)	0.049*** (0.009)	0.049** (0.022)	0.049** (0.021)
Rainfall (log)		0.003 (0.002)	0.003 (0.003)	0.003 (0.002)	0.003 (0.003)	-0.000 (0.003)
Spike in diesel price (%)		0.142 (0.112)	0.142 (0.177)	0.142** (0.042)	0.142 (0.179)	0.165 (0.176)
Monthly time dummy	No	Yes	Yes	Yes	Yes	Yes
Common time trend	No	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	No	Yes	Yes	Yes	Yes	Yes
Market fixed effect	No	Yes	Yes	Yes	Yes	Yes
Region × monthly time dummy	No	No	No	No	No	Yes
Observations	1290	1276	1276	1276	1276	1276
R ^{2b}	0.000	0.225	0.225	0.225	0.377	0.561

Note: $P_{i,t}$ is the auction prices of tea in period t in auction center i . Robust standard errors in parentheses (columns 1–4). In column (3), standard errors are clustered by quarters to correct for temporal dependence and in column (4), it is clustered by auction centers to correct for spatial dependence. In column (5), Driscoll and Kraay standard errors are presented in parentheses to correct for heteroscedasticity, autocorrelation, and contemporary correlation. Diesel prices and domestic auction prices deflated by the wholesale price index at 2012 prices.

^a World tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices.

^bColumn (6) presents within R^2 .

*Significant at 10% level, **significant at 5% level, and ***significant at 1% level.

seasonality, we find that electronic markets have a significant and negative effect on month-on-month changes in tea prices (columns 2–6). Standard errors are clustered by quarters in column (3) to correct for temporal dependence and by auction centers in column (4) to correct for spatial dependence. In columns (5) and (6), we present the main results with Driscoll and Kraay standard errors. We also show the estimates accounting for structural breaks in column (2) of Table A6 in the Supporting Information: Appendix. The results stay robust even after controlling for a structural break. The results suggest that electronic markets reduced spikes in tea prices by about 2.4% than when tea auctions were conducted physically. The reduction in spikes in tea prices has important implications for investors in the tea market. The decrease in price volatility reduces uncertainties for buyers, sellers, and tea producers and helps in making informed decisions about investments. Further, the coefficients of the control variables suggest that a spike in tea production (or supply shocks) and an increase in world tea prices have a positive and significant effect on spikes in tea prices in domestic markets.

5.3 | Relationship between electronic markets and price dispersion

Table 4 presents different fixed effect specifications of Equations (3) and (4), where we analyze the effects of the electronic marketplace between pairs of auction centers on the log of absolute price dispersion and changes in efficiency over time. We interpret the results in columns (1)–(7) as the initial effects of the introduction of electronic markets on market efficiency, while in column (8) the coefficient of the dummy variable Pan-Indian electronic transaction is interpreted as changes in market efficiency over time owing to a further reduction in search cost. For the estimations in columns (1)–(7), we limit the data up to May 2016, while in column (8), we use the full sample from January 2000 to December 2017. When electronic markets were introduced, the price dispersion between auction centers increased initially (columns 1–7). Excluding the factors affecting price dispersion between markets, column (1) shows that the price dispersion between markets has increased by 13%. In column (2), control variables that affect price dispersion between markets, such as world tea prices, dispersion in arrivals between markets and the average rainfall in tea-growing regions, and the spike in diesel prices, are included. Here, we also include a series of dummy variables to control for seasonality, market-pair fixed effects, common time trends, and quadratic time trends to control for nonlinear trends. Group-specific time trends are also included in column (3). Columns (2) and (3) suggest that controlling for other factors, the introduction of electronic marketplaces increased price dispersion by about 20%. In column (4), a lagged dependent variable is added to allow for the previous period's market performance to affect market performance at time t , and it shows that the introduction of the electronic marketplace increased price dispersion by 14%.

To address the spatiotemporal dependence, the standard errors are clustered by quarters in column (5) and by markets in column (6). In column (7), Driscoll and Kraay's standard errors are presented. The results are still positive and statistically significant at the 10% level. Finally, in column (8), we present the change in market efficiency over time. After June 2016, price dispersion between markets was reduced when electronic trading was made flexible to further reduce search costs. In Table A8 in the Supporting Information: Appendix, we present two more specifications with an interaction between dummy variables indicating whether the two auction markets are in the same region and monthly time dummies to control for varying seasonality across different regions of tea production. In Table A9 in the Supporting Information: Appendix, we present the results of Equations (3) and (4) without the absolute auction arrivals between markets as a control variable. These results are much similar to the results presented in columns (7) and (8) in Table 4. This suggests that initially when electronic marketplaces were introduced, the price dispersion between markets increased by 11%–14%; however, after the introduction of the Pan-Indian electronic auction, which further reduced market friction for users, the market efficiency increased, and price dispersion reduced by about 16%. This is probably because when electronic marketplaces were first introduced, they did not eliminate search costs for all market actors. Heterogeneity in buyers' ability to adopt a new technology probably increased the search cost for a few users. These results are similar to the results of Brown and Goolsbee (2002), where they found that Internet-induced reduction in search cost first increased price dispersion on the introduction of electronic marketplaces and later decreased in the case of term life insurance markets.

6 | CONCLUSION AND POLICY IMPLICATIONS

Asymmetric price information and costly searches often restrict actors in the market from undertaking optimal arbitrage, which results in a wide variation in the prices of agro-based commodities across regions and seasons. The emergence of electronic marketplaces, which connect buyers directly to sellers through a digital platform, promises to be an important tool to reduce search costs and make markets efficient. Although there is a vast literature on the implications of mobile phone technology and MIS on agriculture market performance, there is perhaps only one empirical study that analyses the effects of electronic markets in the context of an LMIC. Thus, this study adds to this sparse literature through a case study of the tea sector in India.

TABLE 4 Effects of electronic markets on price dispersion.

	Dependent variable $[\log P_{it} - P_{rit}]$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Both markets have electronic marketplace (dummy)	0.141** (0.054)	0.201*** (0.049)	0.209*** (0.049)	0.138*** (0.046)	0.138*** (0.053)	0.138*** (0.020)	0.138*** (0.068)	0.114* (0.069)
Pan India electronic trading (dummy)								-0.271*** (0.098)
World tea price index ^a (log)		0.358*** (0.086)	0.354*** (0.086)	0.211*** (0.080)	0.211*** (0.104)	0.211* (0.119)	0.211* (0.126)	0.224* (0.124)
Absolute arrivals dispersion between markets (log)		0.009 (0.015)	0.012 (0.015)	-0.013 (0.015)	-0.013 (0.016)	-0.013 (0.012)	-0.013 (0.017)	-0.018 (0.016)
Average rainfall in tea growing regions (log)		0.000 (0.021)	-0.000 (0.021)	-0.000 (0.020)	-0.000 (0.021)	-0.000 (0.020)	-0.000 (0.022)	-0.012 (0.023)
Spike in diesel price		0.389 (0.371)	0.398 (0.374)	0.245 (0.360)	0.245 (0.527)	0.245 (0.295)	0.245 (0.511)	0.328 (0.515)
Lagged absolute price dispersion (t - 1) (log)				0.364*** (0.032)	0.364*** (0.041)	0.364*** (0.031)	0.364*** (0.041)	0.379*** (0.040)
Monthly time dummy	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common time trend	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Square of common time trend	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 4 (Continued)

	Dependent variable $[\log P_t - P_{all}]$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	2954	2934	2934	2933	2933	2933	2933	3217
R^2 ^b	0.497	0.668	0.676	0.719	0.719	0.719	0.445	0.453

Note: In columns (1–7), regressions are conducted for the period January 2000 to May 2016.

Robust standard errors in parentheses (columns 1–6). In column (5), standard errors are clustered by quarters to correct for temporal dependence, and in column (6), it is clustered by auction centers to correct for spatial dependence. In columns (6) and (7), Driscoll and Kraay standard errors are presented in parentheses to correct for heteroscedasticity, autocorrelation, and contemporary correlation.

^aWorld tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices.

^bColumns (7) and (8) present within R^2 .

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Using market-level monthly panel data from 2000 to 2017, this study provides empirical evidence on the relationship between electronic markets and the market performance of a limited storable agro-based commodity (tea) in India. Consistent with the consumer search theory, the fixed effect results suggest that the introduction of electronic marketplaces reduced tea prices by 2.1%. Additionally, we find that electronic markets reduced spikes in tea prices by about 2.4%. Further, electronic markets increased price dispersion between markets on the introduction of electronic markets by about 11%–14%; however, price dispersion gradually reduced by about 16%. The findings imply that, in the context of LMICs where digital literacy is low, differences in the ability to adopt a new technology initially increase search costs for a few market actors. However, over time, as markets mature and market actors gain more experience, the search cost declines, and markets become efficient.

From a policy perspective, this study has important implications for India. The Indian government introduced the electronic National Agriculture Markets (e-NAM) in 2016 with an aim to reform the existing agriculture marketing systems and offer producers market access across the country through electronic trading. Similar to the electronic marketplace introduced in the tea market, nearly 1000 wholesale agriculture markets out of 2477 markets have been digitized. Our findings indicate that switching from physical to electronic marketplaces can increase market competition and efficiency for some storable agricultural products. Therefore, from a policy perspective, to maximize the sum of seller revenue and buyer profits, sellers must be able to increase sales by accessing new markets or increasing reservation prices through product differentiation based on quality. Thus, digital platforms that connect buyers to sellers must have a reliable system to sample, grade, and value the products being sold electronically. This is particularly important for products that buyers may not be able to physically inspect before buying. A lack of trust can lead to reduced sales and revenues for sellers, as well as a loss of potential customers.

This study has two limitations. First, although fixed effect estimation has been used to control for all unobserved time-invariant factors that could be correlated with the decision to transition from the physical to an electronic marketplace, we could not control for unobserved time-varying factors. Second, given the context of the market under study, the number of cross-sectional units is small.

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DATA AVAILABILITY STATEMENT

Data available on request.

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