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# THE EFFECTS OF DIGITAL TRADING PLATFORMS ON COMMODITY PRICES IN AGRICULTURAL SUPPLY CHAINS[1]

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*Digital platforms for buying and selling agricultural commodities have generated significant interest in the trade literature as a way to link rural communities to the Internet. Yet, the extent to which these digital platforms actually translate into higher commodity prices for producers remains an open research question. We investigate this question by comparing transaction data on trading various grades of coffee from a recently implemented digital platform in India with similar transactions from a physical commodity auction held weekly, and farm-gate prices in the coffee producing regions of India. Although the digital platform prices closely track the physical commodity auction prices, producers obtain significantly higher prices when they sell the commodity through the digital platform rather than at the farm-gate through brokers who operate in their regions. However, coffee grades with higher price volatility and premium coffee grades that require face-to-face interactions to verify quality obtain lower prices on the digital platform. Our results also indicate that market participants who control the transaction obtain better prices. We discuss the implications of our findings for governments and platform providers.*

**Keywords**: Digital divide, digital platforms, global IT, commodity auctions, bargaining power, commodity trading

## Introduction

During the past decade, numerous innovative information technology applications have emerged around the world to improve agricultural and other rural supply chains. Examples include the online eChoupal platform in India that is used by farmers to sell agricultural commodities (Kumar 2004; Upton and Fuller 2004), online cooperatives of trades people in South America to directly sell products to end consumers (Romero 2000), and trading websites for cattle ranchers in North America (Bearden 2004). In many parts of the developing world, agricultural commodities such as wheat, rice, tea, coffee, and soybeans have been sold through oral auctions for many decades and perhaps even centuries (Banerji and

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Meenakshi 2004). In an effort to improve efficiency, agricultural auctions have also recently been experimenting with digital trading formats. The common purpose of these initiatives is to provide timely price information, disseminate farming knowledge, eliminate intermediaries, and transform the agricultural supply chains that support the livelihood of billions of people around the world.

Empirical research on the impacts of information technology on agricultural supply chains in developing countries is sparse. Although online trading of agricultural commodities has been prevalent in the developed world (Schrader 1984), it is relatively new in the developing world, and data for empirical analysis have not been readily available. However, there are several unanswered and important research questions for policy formulation: What is the magnitude of benefits from digital platforms? Who appropriates the benefits? What are the types of commodities that are suitable for online trading? What is the role of the private sector in providing the platform?

We evaluate the impacts of IT on the coffee supply chain in India. Specifically, we compare transactions of various grades of coffee sold through a recently commissioned digital trading platform in India, with similar transactions from the regulated physical auction held weekly by the Indian Coffee Traders Association (ICTA), and farm-gate prices from the coffee producing regions of India. The digital platform is operated by ITC Limited, a large conglomerate in India with annual revenues in excess of $3 billion. The physical ICTA coffee auctions are held weekly in the city of Bangalore, located near the major coffee producing regions of India. Farm-gate prices are the prices that producers obtain if they choose to sell the coffee through intermediaries who operate in their region.

We answer two questions that have considerable practical relevance and policy implications. First, *can producers benefit from the digital trading platforms through higher prices for agricultural commodities*? To answer this question, we compare prices in the digital platform with farm-gate and physical ICTA auction prices for the same grade of coffee. Second, *what factors affect the differences in price between the digital and physical trading platforms for agricultural commodities*? In our sample, coffee grades vary significantly in terms of price volatility, market size, and the need to verify quality through physical inspections. Further, buyers and sellers vary in terms of their experience and role in the agricultural supply chain. Transactions also vary in size and format. We empirically evaluate the effects of these factors on the difference in price between the two trading formats.

Our research contributes to the burgeoning IS literature on the use of IT in developing countries (Braa et al. 2007; Puri 2007; Silva and Hirschheim 2007) and the digital divide (Payton 2003) in four ways. First, while some have argued that IT can integrate global supply chains and reduce poverty in developing countries (Quibria et al. 2003; Walsham et al. 2007), others are more skeptical that the benefits reach the rural communities (Anonymous 2005). Our research sheds light on this debate by evaluating the impact of the digital trading platform on commodity prices in the agricultural supply chain. Second, although existing studies on the use of IT in developing environments have mainly utilized interpretive and qualitative approaches (Miscione 2007; Puri 2007), our research utilizes a quantitative analysis of transaction data and provides needed diversity in the research methods. Third, while existing research on IT use in the developing world has primarily focused on multinational corporations (Jarvenpaa et al. 2004), we focus on the impact of IT on the agricultural supply chain. Fourth, while numerous empirical studies have examined familiar business-to-consumer (B2C) and consumer-to-consumer (C2C) platforms such as Yahoo and e-Bay (Bailey 1998; Brynjolfsson and Smith 2000), we examine a novel environment for the trading of agricultural commodities that has received limited research attention. This environment is also fundamentally different from the familiar contexts in the developed world, making it difficult to extrapolate results.

The rest of the paper is organized as follows. The next section describes the coffee supply chain in India, and the online and physical trading formats. The subsequent section develops our theory and hypotheses. A description of the data and results of our analyses is then presented. Finally, we summarize our findings, outline future research directions, and conclude the paper.

## Commodity Trading and the Coffee Supply Chain

### *Coffee Grades*

Coffee beans are traded in two forms: *raw* and *clean*. Based on the bean type (Arabica and Robusta) and the type of on-farm processing, there are four types of *raw* coffee beans that are traded: (1) *Arabica Parchment*, (2) *Arabica Cherry*, (3) *Robusta Parchment*, and (4) *Robusta Cherry*. After on-farm processing, the raw coffee beans are further processed at one of the licensed curing works to produce several *clean* coffee grades. Each clean coffee lot is graded using international standards into several sub-grades based on the bean size and the percentage and type of imperfections present. Thus, each *clean* coffee lot is designated by a primary grade that indicates the bean type (Arabica Parchment, Arabica Cherry, Robusta Parchment, or Robusta Cherry) and a sub-grade that indicates bean quality (PB, AA, A, AB, B, C, and BBB).

### *The Coffee Supply Chain in India*

Like in many other agricultural commodities, the coffee supply chain in India consists of four major players. *Planters* are the coffee growers and plantation owners. Based on data published by the Coffee Board of India, there are more than 220,000 planters in India and 99 percent of the planters are classified as small growers. *Exporters* are corporations who contract with international trading houses and international roasters to procure coffee locally and transport overseas. The Coffee Board of India website lists 50 major coffee exporters. Thus, the coffee supply chain is highly fragmented on the supply side and relatively concentrated on the buying side. *Intermediaries* such as agents and brokers perform several roles, such as financing the planters, arranging transportation, and consolidating lots from multiple planters. In addition, a few *domestic roasters* produce coffee for the domestic Indian market.

### *Physical and Digital Trading Formats*

Planters can sell the raw coffee beans at the farm-gate to brokers who operate in the region. After the coffee is graded and cured, both planters and brokers sell the clean coffee lots through various coffee auctions. The Indian Coffee Traders Association (ICTA) holds a coffee auction every Thursday in Bangalore, near the coffee producing regions of southern India. The ICTA auction trades only in clean and graded coffee beans. Planters and brokers carry a sample of the clean coffee to the auction where the lots are sold through oral, ascending bid, English auctions. The ICTA auction sells approximately 31,000 metric tons of coffee annually, which accounts for 10 percent of the total coffee production in India. The typical lot size for the coffee sold through the ICTA auction is about two metric tons. The sellers in the ICTA auctions are typically planters and brokers, whereas the buyers are exporters, domestic roasters, and their agents.

ITC started the digital platform in 2002 and the platform currently sells approximately 5,000 metric tons of coffee annually (both raw and clean grades). ITC authenticates all users as bona fide participants and, in some cases, the participants also deposit margin money to ensure that they have the resources to settle a dispute. In addition, the platform website also provides access to weather forecasts, best practices and expert advice, trade articles, and coffee prices in the domestic and international markets. Sellers are typically larger planters and their intermediaries, while buyers are exporters, domestic roasters, and their agents.

## Theory and Hypotheses Development

### *Price Differences in the Alternative Trading Formats*

The law of one price is a fundamental principle in economics and deviations can reveal interesting information about the alternative trading structures. The literature in diverse disciplines such as finance (Kamara 1988; Meulbroek 1992), economics (Cammack 1991), marketing (Eliashberg et al. 1986), and information systems (Brynjolfsson and Smith 2000; Clemons et al. 2002; Kambil and van Heck 1998; H. G. Lee et al. 1999) has examined the reasons behind the price difference of equivalent assets across different markets and channels. We classify the typical reasons into three categories that form the theoretical basis of our hypotheses.

*Increased Bargaining Power:* The literature on negotiations (Bacharach and Lawler 1981), joint ventures (Yan and Gray 2001), and channels (Crook and Combs 2007) has long recognized the impact of bargaining power on the appropriation of benefits in a trade setting. Intuitively, if a trading format significantly alters the bargaining power of a seller or a buyer, the selling price of the product will adjust accordingly.

*Information Asymmetry:* Differences in the information available to participants in alternative trading formats can lead to price differences for the same underlying asset. Numerous studies in Finance on initial public offerings (IPOs) have attributed the price difference between the IPO offering price and subsequent secondary market price to the limited information available at the time of the IPO (P. J. Lee et al. 1999). In the IS literature, Kambil and van Heck (1998) argue that information disparity leads to lower buyer valuations in online Dutch flower auctions. Similar arguments are also made for the online used car market (see H. G. Lee et al. 1999).

*Structural Differences:* Structural differences between the two trading formats can also lead to different prices for the same asset. Kamara (1988) attributes the price differential between forward and futures contracts for Treasury bills to the immediacy and lower default risk in the futures market. Meulbrook (1992) provides similar arguments for the difference in price between forward and futures contracts on Eurodollars. The IS literature also argues that differences in transaction risk in alternative formats can affect price (Ba and Pavlou 2002).

### Bargaining Power and the Farm-Gate Price of Commodities

Bargaining power refers to a focal entity's ability to win concessions from the other parties involved in a negotiation and gain favorable outcomes. The literature identifies two major sources of bargaining power: the ability to walk away from a deal because the participant has other alternatives (Yan and Gray 2001), and the control of critical resources, such as money, expertise, and technology (Pfeffer 1981).

When planters sell their commodity at the farm-gate through brokers who operate in their regions, they have a limited number of buyers for their product. Further, exporters control extensive and established physical procurement channels in commodity producing regions, consisting of intermediaries who procure on their behalf. In addition, intermediaries in the physical channel appropriate a portion of the profits in exchange for providing immediate liquidity and convenience. On the other hand, the digital trading format increases the bargaining power of planters by providing access to a wider range of buyers, and by reducing their reliance on the established procurement channels and traditional intermediaries. Consequently, planters obtain a higher price when they sell the commodity on the digital platform rather than at the farm-gate through the few brokers who operate in their region.

> ***Hypothesis H1***: *Digital platform prices will be higher than the corresponding farm-gate prices for the same commodity grade.*

### Information Asymmetry and Premium Commodity Grades

Koppius et al. (2004) examined the effects of product representation at a large Dutch flower auction that had implemented on-screen trading and found that deficiencies in online product representation led to reduced flower prices. Kambil and van Heck also documented a negative reaction from buyers to online representation of flower lots in Dutch flower auctions. This negative reaction arises partly because the grading scheme for flower lots is too broad and the nature of the product precluded conveying meaningful quality information in the online markets (Kambil and van Heck 1998). In contrast, the well-defined grading scheme for commercially traded coffee beans can significantly reduce (but does not eliminate) the quality risk in online transactions.

Table 1 shows the different coffee grades in our transaction dataset. Determination of the four major bean types (Arabica Parchment, Arabica Cherry, Robusta Parchment, and Robusta Cherry) is unambiguous. Within each major bean classification, the sub-grades for clean coffee are based on bean size and the percentage of imperfections present, with some possibility of mis-classification. The higher priced sub-grades (PB, AA, A, and AB ) within each of the four major bean classifications are considered to be premium sub-grades of coffee, and the quality risk is higher for these sub-grades when procuring from the online auction. It is important to point out that the grading scheme does not specify other factors such as color, texture, and aroma that may be important to the buyer when procuring premium coffee grades. Thus, the lack of face-to-face interaction and the inability to physically verify quality could negatively affect confidence in the transaction (Ba and Pavlou 2002; Hu et al. 2004; Pavlou and Gefen 2004). This reduces buyer valuation and price for premium grades at the digital platform.

> ***Hypotheses H2:*** *Digital platform prices will be lower than the corresponding physical platform prices for premium commodity grades.*

### Structural Differences: Digital Format as a Secondary and Upstream Market

Participant heterogeneity is widely recognized in the online B2C context in the developed world (Bapna et al. 2004). In developing countries where Internet penetration is lower, it is reasonable that with highly fragmented sellers in commodity supply chains, only the more sophisticated sellers (larger planters and established intermediaries) may participate in the digital trading platform. Thus, we envision that the digital platform is a *secondary* market that operates *upstream* in the agricultural supply chain. Sellers are likely to be intermediaries who procure from the physical channels and sell consolidated lots in the digital trading format. Some sellers could also be larger and more sophisticated planters who sell directly to the exporters. Exporters may also sell the excess coffee they do not require through the digital trading platform.

Our dataset provides indirect evidence to support this observation. With 220,000 planters and 290,000 metric tons of coffee produced annually (Anonymous 2008), the average output per planter is approximately 1.3 metric tons. Similarly,

**Table 1. Descriptive Statistics for Raw and Clean Coffee Grades**

| Coffee Grade: Bean Type | Sub-Grade | Mean ICTA or Farm-Gate Price (INR/Kg) | Std Dev of Price (% of Mean Price) | Number of Digital Transactions | Digital Transaction Volume (Kgs) | Premium Grade |
|---|---|---|---|---|---|---|
| **RAW COFFEE GRADES** | | | | | | |
| Arabica Parchment | RAW | 84.9 | 4.9% | 35 | 299969 | No |
| Arabica Cherry | RAW | 42.5 | 7.2% | 26 | 154891 | No |
| Robusta Parchment | RAW | 69.6 | 8.6% | 62 | 571674 | No |
| Robusta Cherry | RAW | 35.4 | 5.9% | 53 | 530631 | No |
| **CLEAN COFFEE GRADES** | | | | | | |
| Arabica Parchment | PB | 130.36 | 3.3% | 64 | 219573 | Yes |
| Arabica Parchment | AA | 114.48 | 3.3% | 31 | 235758 | Yes |
| Arabica Parchment | A | 112.42 | 3.3% | 66 | 248255 | Yes |
| Arabica Parchment | B | 101.55 | 5.7% | 52 | 242405 | No |
| Arabica Parchment | C | 95.51 | 5.0% | 39 | 193302 | No |
| Arabica Parchment | BBB | 76.82 | 7.5% | 9 | 24640 | No |
| Arabica Cherry | PB | 89.58 | 3.8% | 14 | 23560 | Yes |
| Arabica Cherry | AA | 98.32 | 5.9% | 8 | 14203 | Yes |
| Arabica Cherry | AB | 93.67 | 6.3% | 16 | 89426 | Yes |
| Arabica Cherry | C | 73.71 | 7.5% | 12 | 77226 | No |
| Arabica Cherry | BBB | 67.48 | 5.1% | 15 | 83260 | No |
| Robusta Parchment | PB | 81.89 | 4.8% | 13 | 105111 | Yes |
| Robusta Parchment | AB | 88.39 | 5.6% | 9 | 66625 | Yes |
| Robusta Parchment | C | 74.82 | 5.3% | 13 | 121894 | No |
| Robusta Parchment | BBB | 69.14 | 4.7% | 14 | 114663 | No |
| Robusta Cherry | PB | 73.84 | 5.3% | 57 | 225580 | Yes |
| Robusta Cherry | AA | 77.44 | 4.6% | 46 | 175895 | Yes |
| Robusta Cherry | AB | 74.69 | 5.2% | 38 | 373386 | Yes |
| Robusta Cherry | C | 72.83 | 5.1% | 20 | 98425 | No |
| Robusta Cherry | BBB | 70.00 | 5.6% | 26 | 310834 | No |

Notes: Data shown are for only those clean coffee grades in our transaction set which could be matched to the ICTA auction data reported by the Indian Coffee Board. Mean price is the average ICTA price (2007) for clean coffee grades and the average farm-gate (2007) price for raw coffee grades. Standard deviations of weekly ICTA prices (2007) for clean coffee grades and weekly farm-gate prices for raw coffee grades are shown as a percentage of mean price. INR is Indian Rupees. Approximately 48 INR = $1.00.

the average lot size of transactions in the physical ICTA auctions is approximately two metric tons (the data is available on the website of the Indian Coffee Board). On the other hand, the average lot size in the digital platform (see Table 2) is approximately six metric tons. The difference is statistically significant based on a t-test ($t = 18.93$, $p = 0.001$), indicating that lots are being consolidated on the digital platform. Further, buyers in 58 percent of the transactions in the digital platform also participate as sellers, indicating that buyers often use the digital platform to sell excess lots. These facts indicate that the digital platform functions as a secondary and upstream market for consolidated and excess lots.

The secondary and upstream nature of the digital platform implies that commodity grades that have high price volatility will have greater supply on the digital platform.[2] In the trading of commodities, price volatility (variation of price

[2]We are grateful to two anonymous reviewers for pointing us to this explanation of our findings.

**Table 2. Descriptive Statistics for Digital Platform Data**

| | | | |
|---|---|---|---|
| **Transaction Characteristics** | | | |
| Number of Transactions | 881 | Number of Sell transactions | 678 (77%) |
| Mechanism: Click and Book | 793 (90%) | Number of Buy transactions | 203 (23%) |
| Mechanism: Order Book Mgt. | 15 (1.7%) | Average Transaction Value (INR) | 548,013 |
| Mechanism: Standard Auction | 73 (8.3%) | Average Lot Size (Kg) | 6086 |
| **Participant Information** | | | |
| Number of Distinct Buyers | 88 | Number of Distinct Sellers | 121 |
| Transactions per buyer (Mean) | 10 | Transactions per seller (Mean) | 7.3 |
| Number of Traders | 34 | | |
| **Coffee Grade Information** | | | |
| Raw coffee grade transactions | 177 | Clean coffee grade transactions | 704 |
| Number of bean types | 4 | Number of clean (raw) coffee grades | 29 (4) |

Notes: Traders are those who both buy and sell through the digital platform.

within a period) is indicative of its demand and supply uncertainty (Combes and Guillaumont 2002; Kilima et al. 2008; Morgan 2001). For commodity grades that have unstable demand and supply, exporters cannot reliably estimate the demand, and will carry excess inventory to compensate for the uncertainty (Anupindi et al. 1999). Further, high price volatility could also induce exporters to hedge against price increases by procuring in excess when prices are low. The digital platform provides a convenient secondary market to sell excess lots. Thus, commodity grades with high price volatility will have a greater supply on the digital platform, leading to lower online prices for such commodities.

We note that the price volatility of a commodity can also be indicative of valuation uncertainty (Kazumori and McMillan 2005). If the valuations of commodity grade are consistent, the variance in price will be small. However, when grade definitions are ambiguous, the price of the same grade can vary significantly based on characteristics not adequately captured by the grade definitions. The ability to inspect visually is an advantage in the physical platform, and price on the digital platform will be lower for such commodity grades. Although both of these arguments support the following hypothesis, we argue in the results section that the former interpretation of price volatility is more applicable.

> ***Hypothesis H3**: Digital platform prices will be lower than the corresponding physical platform prices for commodity grades with high price volatility.*

### *Structural Differences: Lower Transaction Cost of the Digital Platform*

It is well recognized that transaction costs are lower in the digital format for several reasons (Bakos 1997; Pinker et al. 2003). Participants do not incur the travel related costs associated with the physical ICTA auctions, while the daily operations of the digital format reduce wait times and increase trading efficiency (Kamara 1988). However, it is not immediately clear whether buyers or sellers will appropriate the benefits of digital trading.

The digital platform can have both "buy" and "sell" transactions initiated by buyers and sellers, respectively. In sell transactions, sellers post the commodity that they want to sell. In buy transactions, buyers post the commodity they want to procure. The *primary participant* is the originator of the transaction—the buyer for buy transactions and the seller for sell transactions. We argue that the *primary participant* of a transaction will appropriate most of the benefits of digital trading. The bargaining literature demonstrates that control over key resources and the ability to wait are important determinants of outcome in negotiations (Yan and Gray 2001). The low transaction cost and daily operations of the digital platform make it possible for the primary participant to post the transaction repeatedly at low cost and for extended periods to obtain a favorable price. For example, a buyer (seller) can post a low (high) price and wait to find a seller (buyer) willing to sell (buy) at that price. This ability to control the transaction without cost and wait for a favorable outcome provides an advantage to the primary participant (Yan and Gray 1994), implying that buy transactions (initiated by the buyer) will obtain a lower price and sell transactions (initiated by the seller) will fetch a higher price in the digital format. That is, the primary participant obtains a larger share of the benefits from digital trading.

> ***Hypothesis H4***: *Digital platform prices for the same commodity grade will be higher for sell than for buy transactions.*

## Data and Results

### The Data Set

Data for the empirical analysis were obtained from two sources. In March 2002, ITC Limited started operating the digital platform for coffee trading described earlier in the paper. The company provided us with 20 months of transaction data for all transactions completed on the digital platform between January 2007 and August 2008. Since the digital platform had been in operation for over five years at that time, the platform was reasonably stable. There were 881 completed transactions during that period. The available data contained the buyer and seller identifiers, coffee grade, unit price (INR/Kg),[3] lot size (Kg), transaction type (buy or sell), trading mechanism (click and book, order book management, and standard auction), and transaction date. The transaction data included *raw* and *clean* (cured and graded) coffee lots. Table 1 shows descriptive statistics for coffee grades in our transaction set from the digital platform. Table 2 presents some of the major characteristics of the digital platform transactions.

We also obtained data on *each* week's ICTA physical auctions held during the time-period of our study from the Coffee Board of India publications available at their website (www.indiacoffee.org). These publications are newsletters that provide, along with other analyses, the average closing price for each clean coffee grade (INR/Kg) traded at each weekly ICTA auction. The publications also provide average farm-gate prices each week for *raw* coffee grades. These two data sources allowed us to match and compare commodity prices in physical and digital trading formats.

[3]INR is Indian Rupees. Approximately 48 INR = $1.00 U.S.

### Matching Digital Platform Transactions with Physical Platform Data

To evaluate our hypotheses, we matched every digital platform transaction with the appropriate physical platform data. Specifically, digital transactions for clean coffee grades were matched with the immediately previous weekly ICTA auction data for the exact same coffee grade. Likewise, digital transactions for raw coffee grades were matched with farm-gate prices for the exact same raw coffee grade for the immediately preceding week. Of the 881 digital transactions in our database, 738 (see Table 1) were for coffee grades that matched the coffee grades covered in the Coffee Board publications, while the remaining transactions were for specialty grades or had ambiguous grade information recorded. Of these 738 transactions, physical trading format price information (ICTA auction or farm-gate price) for the immediately preceding week was available for 688 transactions, since the Coffee Board publications did not record prices for all coffee grades every week. These matched 688 digital platform transactions form our primary data set for price comparisons.

### Overall Price Difference between the Two Trading Formats

Table 3 shows the mean and median price difference for the whole sample and specific subsamples. In our analysis, a specific combination of bean type (Arabica Parchment, Arabica Cherry, Robusta Parchment, and Robusta Cherry) and sub-grade (PB, AA, A, B, C, BBB, or RAW) is a coffee grade. For each digital platform transaction, we calculate ($se_g - sp_g$) where $se_g$ is the unit price of coffee grade g for the digital platform transaction, and $sp_g$ is the unit price of coffee grade g in the physical trading platform during the immediately preceding week. The subsamples in Table 3 are for selected categorical variables relevant to our hypotheses.

The average price difference between the digital and physical trading formats for the whole sample is small (0.3 percent) and marginally significant. However, for transactions involving raw coffee grades, digital platform prices are 3.3 percent higher than the farm-gate prices and the difference is statistically significant at the 1 percent level based on a two-tailed test, providing preliminary support for Hypothesis H1. Further, digital platform prices for premium coffee grades are 1.1 percent lower than physical platform prices (significant at the 1 percent level), whereas digital platform prices are 2 percent higher than physical platform prices for non-premium coffee grades (significant at the 1 premium level). This provides preliminary support for hypothesis H2. Also, Table 3

**Table 3. Price Difference between Digital and Physical Platforms**

| Subsample | Size | Mean $(se_g - sp_g)/sp_g$ | Median $(se_g - sp_g)/sp_g$ |
|---|---|---|---|
| Whole Sample | 688 | 0.3% (1.9)* | 0.5% (3.5)*** |
| Raw Coffee Grades | 170 | 3.3% (12.8)*** | 3.4% (9.6)*** |
| Clean Coffee Grades | 518 | -0.6% (-3.6)*** | -0.2% (-2.8)*** |
| Sell Transactions | 529 | 0.7% (4.7)*** | 0.9% (5.4)*** |
| Buy Transactions | 159 | -1.2% (-2.8)*** | -1.0% (-2.5)** |
| Premium Grades | 365 | -1.1% (-4.7)*** | -0.9% (-4.6)*** |
| Non-premium Grades | 308 | 2.0% (9.0)*** | 2.1% (8.9)*** |

Notes: 2-tailed significance at the ***(1%), **(5%), and *(10%) levels. t-values in parenthesis. t-values for the median price difference are from the Wilcoxon signed rank test.

shows that prices are almost 2 percent higher for sell transactions than for buy transactions (significant at the 1 percent level), providing preliminary support for hypothesis H4.

### Notation

Before describing the empirical model, we introduce the following notation, which relates to a specific online transaction in our data set for coffee grade g.

| | |
|---|---|
| $P_g$ | Indicator variable that is set to 1 if coffee grade g is a premium coffee grade, 0 otherwise |
| $CV_g$ | Coefficient of variation of price (standard deviation/mean price) of coffee grade g at ICTA auctions (clean grades) or at farm-gate (raw grades) over a one-year period |
| $se_g$ | Selling price for coffee grade g at the digital platform auction (INR/Kg) |
| $sp_g$ | Previous week's physical ICTA auction price for clean grades or previous week's farm-gate price for raw grades (INR/Kg) |
| S | Indicator variable that is set to 1 if the transaction is a sell transaction, 0 otherwise |
| $R_g$ | Indicator variable that is set to 1 if the transaction is for a raw grade, 0 otherwise |
| Q | Lot size of the digital platform transaction (metric tons) |
| ST | Indicator variable set to 1 if the seller in the online transaction also participates in the digital platform as a buyer in another transaction (informed traders), 0 otherwise |
| SE | Number of digital transactions executed by the seller during the time period of the study as a proxy for seller experience |
| BT | Indicator variable set to 1 if the seller in the online transaction also participates in the digital platform as a buyer in another transaction (informed traders), 0 otherwise |
| BE | Number of digital transactions executed by the seller during the time period of the study as a proxy for seller experience |
| CB | Dummy variable to indicate click and book transaction (standard auction is base case) |
| OB | Dummy variable to incorporate order book management transactions (standard auction is base case) |
| $M_x$ | Month dummy variable to incorporate time fixed effects (x = 1 is base case) |
| $B_k$ | Dummy variable for each bean type (k=1 is the base case) |
| $V_g$ | Annual digital trading volume for coffee grade g (kilo tons) |

### Control Variables in the Model

We incorporate several control variables in the regression models to ensure that the results of our data analyses are not biased by omitted variables. We introduce a control variable Q in the model that represents the lot size (metric tons) of a transaction in the digital platform to consider the impact of lot size on the price difference. Larger lot sizes can positively affect the price difference, since buyers are likely to value larger lots more. On the other hand, larger lots can also incorporate volume discounts that negatively affect the price difference.

Since intermediaries also buy and sell through the digital platform, some of the sellers (buyers) in our online transaction data set also participated as buyers (sellers) in other transactions. Since such sellers and buyers may be more informed traders than others who perform a single role, we use control variable ST (BT) that is set to 1 if the seller (buyer) in a transaction also participates in the digital platform as a buyer (seller), 0 otherwise.

Learning curve effects imply that buyers and sellers with greater experience on the digital platform will extract greater benefits from online trading (Argote 1999). To capture this effect, we include a control variable SE (BE) that represents the total number of transactions executed by the seller (buyer) during the time-period of the study, as a proxy for seller (buyer) experience.

The digital platform provides three mechanisms for trading: (1) *click and book* (90 percent of transactions), where the seller lists the coffee grade and quantity and the buyer concludes the transaction by clicking acceptance, (2) *order book management* (2 percent), where the buyer can buy a specific quantity instead of the whole lot offered for sale, and (3) *standard auction* (8 percent), which mimics the ICTA auction format online with daily auctions starting at 10:30 a.m. We include two dummy variables (CB and OB) to indicate whether the transaction is a "click and book" or "order book management" transaction, with "standard auction" as the base case.

We also include dummy variables for each month of the year ($M_2$ – $M_{12}$) with the first month ($M_1$) as the base case to control for any seasonality related effects on our results. Also, to incorporate systematic differences between the four major bean types (Arabica Parchment, Arabica Cherry, Robusta Parchment, and Robusta Cherry), we include dummy variables to indicate the bean type ($B_k$). Finally, since the market size of a commodity can affect the number of buyers and hence the price difference, we incorporate the total volume (by weight) of digital platform transactions ($V_g$) for coffee grade g as a control variable.

## Regression Model

In the commodity supply chain in developing countries, the needs of the international markets affect commodity prices and the buyer (exporter) plays a primary role in determining prices. To take into account the heterogeneity among buyers, we utilize a *buyer random effects* evaluation of the following regression model (A). For robustness, we also test a *seller random effects* evaluation of the regression model (with ST and SE variables replaced by BE and BT, respectively). The results are similar for both models. The Hausman test indicates that the random effects specification is appropriate for the data and there is no systematic difference with parameter estimates obtained through a fixed effects specification.

$$\begin{aligned}\frac{se_g - sp_g}{sp_g} &= \beta_0 + \beta_1 R_g + \beta_2 P_g + \beta_3 CV_g + \beta_4 S \\ &+ \beta_5 Q + \beta_6 ST = \beta_7 SE + \beta_8 CB + \beta_9 OB + \beta_{10} V_g \\ &+ \sum_{k=2\ldots4} \beta_k^B B_k + \sum_{x=2\ldots12} \beta_x^M M_x + \text{Buyer random effects}\end{aligned} \tag{A}$$

$$\begin{aligned}\frac{se_g - sp_g}{sp_g} &= \beta_0 + \beta_1 R_g + \beta_2 P_g + \beta_3 CV_g + \beta_4 S \\ &+ \beta_6 BT + \beta_7 BE + \beta_8 CB + \beta_9 OB + \beta_{10} V_g \\ &+ \sum_{k=2\ldots4} \beta_k^B B_k + \sum_{x=2\ldots12} \beta_x^M M_x + \text{Seller random effects}\end{aligned} \tag{B}$$

In models (A) and (B), the unit of analysis is a single digital platform transaction. The variable $se_g$ is the unit price in the digital platform for a specific transaction, while $sp_g$ is the unit price of coffee grade g in the *immediately* previous ICTA physical auction (clean grades) or the farm-gate price for the immediately preceding week (raw grades). The results are consistent if we match with the immediately following week instead. Thus, for each online transaction, we calculate the price difference as ($se_g – sp_g$) expressed as a percentage of $sp_g$. The notations described earlier explain the other variables in the models.

## Results from the Analysis

Table 4 presents the results for Models A and B. For each of the models, we first enter the control variables (A1 and B1) and then the model variables (A2 and B2). All models are significant at the 1 percent level. The model variables increase $R^2$ from 17.7 percent to 24.5 percent for Model A, and 13.2 percent to 23.0 percent for model B. The coefficient for the $R_g$ variable is significant at the 1 percent level and positive, indicating that the price difference is higher for raw coffee grades. Since digital platform prices for raw coffee grades are compared to farm-gate prices for the same raw grade, our results support hypothesis H1. The coefficients for $P_g$ and $CV_g$ are negative and significant (both at the 1 percent level), indicating that the price difference between the digital and physical platforms is lower for premium coffee grades and for coffee grades with high price volatility. Thus, our results provide support for hypotheses H2 and H3. The coefficient for the S variable is significant and positive (at the 1 percent level), indicating that the price of a commodity on the digital trading platform is greater for sell than for buy transactions, and our results support hypothesis H4. The results

**Table 4. Buyer and Seller Random Effect Model Estimation of Parameters**

| Model Variables | Explanation | Pred Sign | A: Buyer Random Effects | | B: Seller Random Effects | |
|---|---|---|---|---|---|---|
| | | | A1: Control | A2: Full Model | B1: Control | B2: Full Model |
| Intercept | Constant term | +/- | 0.01555 (0.01125) | 0.03854 (0.01564)** | 0.02175 (0.01059)** | 0.04004 (0.01409)*** |
| $R_g$ | Raw grade ($R_g$ = 1) indicator | + | | 0.02827 (0.00714)*** | | 0.031891 (0.00798)*** |
| $P_g$ | Premium grade ($P_g$ = 1) indicator | - | | -0.01921 (0.00485)*** | | -0.01699 (0.00425)*** |
| $CV_g$ | Coefficient of variation of price | - | | -0.52515 (0.17276)*** | | -0.47534 (0.15067)*** |
| S | Sell (S = 1) transaction indicator | + | | 0.01207 (0.0045)*** | | 0.00729 (0.00419)* |
| CB | Click and Book indicator | + | 0.00109 (0.06625) | 0.00212 (0.00642) | 0.0048 (0.06424) | -0.00235 (0.00624) |
| OB | Order Book Management indicator | +/- | -0.01128 (0.01333) | -0.01163 (0.01283) | -0.01221 (0.01268) | -0.00941 (0.01233) |
| ST or BT | Seller/Buyer is a trader | + | -0.00835 (0.00367)** | -0.00208 (0.00368) | -0.00054 (0.00392) | -0.00192 (0.00381) |
| SE or BE | Number of seller/ buyer transactions | +/- | -0.0001 (0.00006) | -0.00002 (0.00006) | -0.00002 (0.00005) | -0.00007 (0.00005) |
| Q | Lot Size (Tons) | +/- | 0.00011 (0.00028) | -0.00001 (0.00027) | 0.00012 (0.00027) | 0.00001 (0.00027) |
| $V_g$ | Market Size for coffee grade (KTons) | +/- | 0.02581 (0.01217)** | 0.01509 (0.01389) | 0.0088 (0.01181) | 0.00792 (0.01261) |
| $M_x$ | Month dummy variables (x=2-12) | +/- | Included | Included | Included | Included |
| $B_k$ | Bean Type dummy variables (k=2-4) | +/- | Included | Included | Included | Included |
| $BB_{bk}$ or $BS_{sk}$ | Bean type buyer and bean type seller dummy variables | +/- | Robustness Check | Robustness Check | Robustness Check | Robustness Check |
| $R^2$ | | | 17.7% | 24.5% | 13.2% | 23.0% |
| Wald | | | 107.8*** | 178.0*** | 59.4*** | 118.8*** |

**Note:** Significance is shown at the ***(1%), **(5%), and *(10%) levels based on a two-tailed test. Standard errors are in parenthesis. Dummy variables for each bean type buyer (Model A) and each bean type seller (Model B) combination were included to check for robustness and do not significantly affect the results.

for Buyer (A) and Seller (B) random effect models are very similar and both models support hypotheses H1 through H4.

In deriving hypothesis H3, we relied on two interpretations of price volatility ($CV_g$). Price volatility can be a measure of demand–supply uncertainty and valuation uncertainty, both of which would lead to lower prices on the digital platform. We believe that the first interpretation of price volatility is more applicable in our context. First, valuation uncertainty is already captured in our empirical models through the $P_g$ variable, and any residual uncertainty is likely to be small. Further, the second interpretation would argue that price volatility would be higher for premium sub-grades ($P_g$ = 1) since valuation uncertainty is higher for such grades (see our rationale for Hypothesis H2). However, in our data set, non-premium sub-grades have a mean $CV_g$ value of 6.2 percent, while premium sub-grades have a mean $CV_g$ value of 4.2 percent (difference significant at the 1 percent level), inconsistent with the second interpretation of price volatility.

We performed two additional robustness checks on the results in Table 4. First, we included dummy variables for each bean type buyer (Model A) and bean type seller (Model B) combination. Further, since the panel data is unbalanced and digital transaction dates may not be selected at random by the participants, we utilized the two-step Heckman selection model to correct for the impact of this selection bias on parameter estimates (Wooldridge 2001). The results remain unchanged from Table 4 and are reported in the online appendix.

## Summary and Implications

In this paper, we compared transactions on a recently commissioned digital coffee-trading platform in India with those in the corresponding weekly physical auctions run by the Indian Coffee Traders Association (ICTA), and with farm-gate prices in the coffee producing regions of India. We find that while the digital platform prices closely tracked the physical ICTA auction prices, they are significantly higher than the farm-gate prices that planters obtain when they sell the commodity through brokers who operate in their regions. Further, digital platform prices were lower for premium coffee grades that benefit from the face-to-face interactions enabled by the physical ICTA auctions, and were lower for commodity grades that have high price volatility. Further, we find that primary participants (originators of the transactions) obtain better prices on the digital platform.

### *Limitations and Future Research*

Before interpreting the results of our study, we discuss some of its key limitations. First, our analysis is restricted to a single commodity with a well-defined grading scheme. While this allows us to isolate the impact of the digital platform on prices, it is difficult to extend the results to other commodities. Further, while we analyze the platform five years after its inception, the steady state behavior of the platform is difficult to predict. The data set available to us includes only completed transactions and we do not have detailed information on platform participants. Thus, in spite of the control variables we have included, participant heterogeneity may affect the results. Further, primary data collection through interviews and observations will provide greater insights on the social and economic benefits of endeavors such as eChoupals.

### *Benefit to Producers from Digital Trading Platforms*

An issue of importance to governments, policy makers and others entrusted with protecting the interests of producers is whether the digital platform will lead to higher commodity prices for rural communities. In our analysis, we find that the price of clean coffee is only marginally higher in the digital platform when compared to the price of the same grade of coffee in the physical ICTA auction. However, for raw coffee grades (of greater relevance to planters), the digital auction price is about 5 percent ($\beta_0 + \beta_1$ estimates in Table 4) higher than the farm gate price for the same bean type. Further, the sell transactions (S = 1) on the digital platform obtained an additional 1.2 percent ($\beta_4$) premium over physical platform prices, indicating that a planter selling raw coffee grades can obtain an estimated 6 percent higher price on the digital platform when compared to the corresponding farm-gate price. To put this value in perspective, we note that the average international price reported by the International Coffee Organization for Arabica clean coffee is approximately INR 130/Kg for 2007 (Anonymous 2010), whereas the corresponding average in our transaction data is INR 119/Kg. Thus, there is an 8 percent margin in this portion of the supply chain, and the 6 percent higher price for raw coffee grades is economically significant.

Two broad strategies will increase benefits of the digital platform to producers. First, actions by governments and platform providers to reduce valuation uncertainty (such as the development of a more precise grading scheme for commodities) will increase the effectiveness of the digital platform and enable producers to obtain better prices. The digital platform is suitable for numerous commodities for which precise grading standards already exist in the developed world, such as wheat, soybean, barley, oats, rye, flaxseed, and corn (for more details, see the U.S. Department of Agriculture website at www.gipsa.usda.gov). Second, the empirical data also suggest that the digital platform functions as a secondary market upstream in the agricultural supply chain. To enable smaller planters to directly participate in this upstream market, the government and platform providers can take several actions. For example, electronic mechanisms to consolidate lots will be beneficial because upstream buyers typically prefer larger lot sizes and the average lot size is significantly higher in the digital platform. Also, the platform providers or the government can create participant authentication schemes to reduce the uncertainty in buying from smaller planters without the face-to-face interaction of the physical trading platform. Finally, planter education and training schemes to provide the skills necessary to participate in the digital platform will increase awareness and participation.

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RESEARCH ARTICLE

# THE EFFECTS OF DIGITAL TRADING PLATFORMS ON COMMODITY PRICES IN AGRICULTURAL SUPPLY CHAINS

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# Appendix

## The Effects of Digital Trading Platforms on Commodity Prices in Agricultural Supply Chains

We performed two additional robustness checks for the results reported in Table 4. First, we incorporated additional dummy variables to capture buyer bean type and seller bean type fixed effects. Second, we incorporated Heckman selection models to correct for some of the potential biases that arise from the unbalanced panel data used in our analysis.

### *Additional Notation*

| | |
|---|---|
| $BB_{bk}$ | Dummy variable for each bean type (k) and buyer (b) combination (k = 1,b = 1 base case) |
| $BS_{sk}$ | Dummy variable for each bean type (k) and seller (s) combination (k = 1, s = 1 base case) |
| $TV_{mk}$ | Overall coffee export volume during month m (kilo tons) |
| $DF_m$ | Fraction of coffee export volume traded on the digital platform during month m |
| $Z_{bd}$, $Z_{sd}$ | Indicator variable set to 1 if buyer b (seller s) had a digital transaction on date d |

### *Buyer-Product and Seller-Product Dummy Variables*

Note that the results in Table 4 incorporate buyer (Model A) and seller (Model B) random effect specifications. The models also incorporate dummy variables for each coffee bean type (Arabica Parchment, Arabica Cherry, Robusta Parchment, and Robusta Cherry). However, it is also possible that buyers and sellers have special expertise in certain types of coffee beans. For example, an exporter (buyer in the digital platform) may supply to international coffee roasters that have a preference for specific bean types. Likewise, a planter may have expertise in growing specific types of coffee beans. To incorporate such expertise differences, we included dummy variables for each bean type buyer (Model A) and bean type seller (Model B) combination ( $BB_{bk}$ and $BS_{sk}$ variables described above). Obviously, STATA automatically drops those dummy variables that do not have at least two corresponding digital platform transactions. The dummy variables do not change the results significantly and the hypotheses are supported in the modified analysis.

## Unbalanced Panel Data and Selection Bias

In our dataset, participants had an average of 10 transactions during the 20-month period of the study, indicating that each participant transacted on only 2.5 percent of the trading days. It is likely that the selection of trading days on the digital platform is entirely random and based solely on whether the participant has coffee lots to buy or sell on a specific day. If the selection of digital transaction dates is indeed random and uncorrelated with the error term, the parameter estimates in Table 4 are consistent (Wooldridge 2001).

However, consider the following situation where selection of transaction dates on the digital platform may not be entirely random. Participants have a choice between trading on the physical and digital platforms. For historical reasons and past familiarity with the physical platform, they may choose to transact on the digital platform only if the price difference between the digital and physical platforms is above a certain threshold or reservation value. This is analogous to the incidental truncation problem described in Wooldridge (2001, p. 578) for estimating the wage equation using a panel of individuals where wage data is only observed during months when the individual is working (that is, the wage is above an unobserved reservation wage for the individual). In such situations, selection for inclusion in the panel may be correlated with the error term and the estimation of parameters using only observed data is likely to be biased (Wooldridge 2001).

As suggested by Wooldridge (p. 582), we utilize the two-step Heckman selection procedure to correct for the impact of this selection bias on parameter estimates. The first stage of the Heckman requires a completely balanced panel of explanatory variables that predict the existence of a transaction on a specific date. We identify two factors that affect the existence of a digital transaction on a specific date First, the volume of coffee traded on the digital platform per month varies between 1 percent and 6.5 percent of total export volume, indicating that there are months in the year when participants find it beneficial to trade on the digital platform. Second, the likelihood of a transaction is higher during times when the overall coffee trading volume is high. Thus, in the first stage of the Heckman model, we use $DF_m$ (fraction of overall coffee export volume traded on the digital platform in month m) and $TV_m$ (total export volume of coffee in month m) as explanatory variables to predict the existence of a digital transaction on a specific date. We constructed a completely balanced panel of the $TV_m$ , $DF_m$, and $Z_{bd}$ ($Z_{sd}$) variables for every buyer (seller) and for every date in the period of the study. The Heckman procedure estimates a logistic regression with $Z_{bd}$ ($Z_{sd}$) as the outcome variable, and $TV_m$ and $DF_m$ as independent variables. In the second stage of the Heckman procedure, the Mills ratio calculated from the logistic regression in the first stage is included as an independent variable, along with the other variables in Models A and B in the paper (Wooldridge 2001). If a participant had more than one transaction on the same day, we spread the transactions within the same month to construct the daily panel data.

The results of the analysis appear in Table A1. As expected, the first stage of the Heckman analysis shows that transactions are more likely to occur during the months when the fraction of coffee traded online is high (the coefficient of the $DF_m$ variable is positive and significant at the 1 percent level). In the second stage, the coefficient for the Mills ratio from stage 1 of the Heckman procedure is not significant indicating that selection bias does not affect the parameter estimates. The coefficients of the focal variables in the models remain almost unchanged from Table 4 and support hypotheses H1 through H4.

**Table A1. Heckman Selection Models with Buyer and Seller Random Effects**

| Model Variables | Explanation | Pred Sign | Buyer Random Effects | Seller Random Effects |
|---|---|---|---|---|
| **Heckman Second Stage** | | | | |
| Intercept | Constant term | +/- | 0.11549 (0.17916) | 0.11472 (0.16842) |
| $R_g$ | Raw grade ($R_g$ = 1) indicator | + | 0.02837 (0.00714)*** | 0.03221 (0.00803)*** |
| $P_g$ | Premium grade ($P_g$ = 1) indicator | - | -0.01918 (0.00485)*** | -0.01696 (0.00425)*** |
| $CV_g$ | Coefficient of variation of price | - | -0.5219 (0.17296)*** | -0.4758 (0.15072)*** |
| S | Sell (S = 1) transaction indicator | + | 0.01219 (0.00451)*** | 0.00718 (0.0042)* |
| CB | Click and Book indicator | + | 0.00205 (0.00643) | -0.00245 (0.00624) |
| OB | Order Book Management indicator | +/- | -0.01184 (0.01284) | -0.00945 (0.01234) |
| ST/BT | Seller/Buyer is a trader | + | -0.00196 (0.00369) | -0.00192 (0.00381) |
| SE/BE | Number of seller/ buyer transactions | +/- | -0.00002 (0.00006) | -0.00007 (0.00005) |
| Q | Lot Size (Tons) | +/- | -0.00001 (0.00027) | 0.00001 (0.00027) |
| $V_g$ | Market Size for coffee grade (KTons) | +/- | 0.01535 (0.01391) | 0.0076 (0.01263) |
| $M_x$ | Month dummy variables (x = 2 – 12) | +/- | Included | Included |
| $B_k$ | Bean Type dummy variables (k = 2 – 4) | +/- | Included | Included |
| Mills Ratio | Mills ratio from Heckman Stage 1 | +/- | -0.03362 (0.07791) | -0.03099 (0.06964) |
| $R^2$ | | | 24.5% | 22.9% |
| Wald $\chi^2$ | | | 177.9*** | 118.68*** |
| **Heckman First Stage** | | | | |
| Intercept | Constant Term in Heckman First stage | | -2.6171 (0.06709)*** | -2.68975 (0.06215)*** |
| $TV_m$ | Total Export Volume in month m (KTons) | | 0.000005 (0.000003)* | 0.000004 (0.000003) |
| $DF_m$ | Fraction of Coffee Traded Online in month m | | 10.14443 (0.89756)*** | 10.45842 (0.90624)*** |

**Notes:** Results from Heckman selection models for Buyer (A) and Seller (B) random effects are shown. Significance is shown at the ***(1%), **(5%), and *(10%) levels based on a two-tailed test. Standard errors are in parenthesis.