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Personalized digital extension services, electronic marketplaces, and mobile phones: Implications of digital technology for rural development in India

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ABSTRACT

In developing countries, the cost of acquiring information is substantially high because information is either limited, unevenly distributed, or inefficiently transmitted. Information problems have important consequences on how individuals and markets behave in the absence of perfect information. Often it results in the inability to carry out mutually beneficial exchange and may lead to inefficiencies in the allocation of resources. Under these circumstances, a key policy question for promoting rural development and poverty reduction in the context of developing countries is: how information constraints faced by rural households can be overcome? One potential mechanism to reduce information constraints is the use of digital technologies, which build on information and communication technologies (ICTs) such as internet platforms and mobile phones. In this context, this dissertation empirically analyses the implications of three types of digital technologies—personalized digital extension services, electronic marketplaces, and mobile phones—on various development outcomes in India, such as agriculture performance, efficiency in agro-based commodity markets, rural off-farm opportunities, and gender outcomes.

The first essay focuses on an example of a digital technology that reduces information barriers on the input-side of farm production. Using primary observational data from India, this essay analyses the effects of personalized digital extension services on smallholder agricultural performance. Here, problems of selection bias in the impact evaluation are reduced through propensity score matching combined with estimates of farmers' willingness to pay for digital extension. The results show that the use of personalized digital extension services significantly increases input intensity, production diversity, crop productivity, and levels of commercialization. Total crop income is increased by 25%.

The second essay explores the effects of using a digital tool to connect buyers and sellers in the output market. Using high-frequency monthly data from 2000 to 2017 and applying a fixed-effects approach with Driscoll and Kraay standard errors to deal with spatial and temporal correlation, this essay provides empirical evidence on the effects of electronic markets on prices, spikes in prices, and price dispersion of an agro-based commodity—tea— in India. Consistent with search theory, the results suggest

that the introduction of electronic markets reduced prices and spikes in tea prices by about 2% between 2000 and 2017. Further electronic marketplaces initially increased price dispersion between markets by about 11-14%, but over time it reduced by 16%.

Subsequently, the third essay analyses the effect of mobile phones on off-farm employment. Using nationally representative panel data from rural India and regression models with household fixed effects and an instrumental variable approach this essay tests the hypothesis that ownership of a mobile phone increases rural households' off-farm employment. The results suggest that mobile phone ownership significantly increases the likelihood of participating in various types of off-farm employment, including casual wage labour, salaried employment, and non-agricultural self-employment. The effects of mobile phones are significant for all types of rural households but tend to increase with the level of remoteness.

Finally, the fourth essay analyses the effects of mobile phones on gender outcomes. In many developing countries informal institutions (social and gender norms), structural impediments (inadequate and poor quality of roads and transport systems), and security considerations often restrict women's mobility. In this context, where women are physically and economically isolated, mobile phones promise to be an effective instrument to connect them to markets and services by improving access to information, mobilizing interpersonal networks, influencing attitudinal attributes, and improving physical mobility. Using nationally representative data from India collected in 2011-12 and applying an instrumental variable approach, the results suggest that mobile phones have a positive and significant effect on women's mobility and access to reproductive healthcare services. The disaggregated analysis suggests that the effect is higher for women from poor households as compared to that of non-poor households. Even for those women who live in a relatively conservative community and are required to exercise seclusion, mobile phones have a significant and positive effect.

ZUSAMMENFASSUNG

In Entwicklungsländern sind die Kosten für die Beschaffung von Informationen wesentlich höher als in entwickelten Ländern, da die Informationen begrenzt, ungleichmäßig verteilt und ineffizient übertragen werden. Informationsprobleme haben wichtige Auswirkungen darauf, wie sich Individuen und Märkte in Abwesenheit perfekter Informationen verhalten. Sie führen häufig dazu, dass ein für beide Seiten vorteilhafter Austausch nicht möglich ist, und können zu Ineffizienzen bei der Allokation von Ressourcen führen. Unter diesen Umständen lautet eine zentrale politische Forderung der ländlichen Entwicklung und der Armutsbekämpfung in Entwicklungsländern: Wie können Informationsbeschränkungen, denen sich ländliche Haushalte gegenübersehen, überwunden werden?

Ein möglicher Mechanismus zur Verringerung von Informationsengpässen ist der Einsatz digitaler Technologien, die auf Informations- und Kommunikationstechnologien wie Internetplattformen und Mobiltelefonen aufbauen. Vor diesem Hintergrund liefert diese Dissertation empirische Belege für die Auswirkungen digitaler Technologien (personalisierte digitale Beratungsdienste, elektronische Marktplätze und Mobiltelefone) auf verschiedene Entwicklungsergebnisse in Indien, insbesondere in den Bereichen:Landwirtschaft, Agrarrohstoffmärkte, ländlicher Off-Farm-Sektor und Geschlechtergleichstellung.
Der erste Aufsatz konzentriert sich auf das Beispiel einer digitalen Technologie, die Informationsbarrieren auf der Input-Seite der landwirtschaftlichen Produktion reduziert. Dieser Aufsatz analysiert die Auswirkungen von personalisierten digitalen Beratungsdiensten auf die landwirtschaftliche Leistung von Kleinbauern auf der Basis von Beobachtungsdaten aus Indien. Hier wurden die Probleme der Selektionsverzerrung in der Wirkungsevaluation durch die Kombination der Methoden des Propensity Score Matching mit Schätzungen der Zahlungsbereitschaft der Landwirte für digitale Beratung reduziert. Die Ergebnisse zeigen, dass die Verwendung personalisierter digitaler Beratungsdienste die Eingangsintensität, die Produktionsvielfalt, die Pflanzenproduktivität und den Grad der Kommerzialisierung deutlich erhöht. Das gesamte Ernteeinkommen stieg um 25%.

Der zweite Aufsatz untersucht die Auswirkungen der Verwendung eines digitalen Tools, um Käufer und Verkäufer auf dem Output-Markt miteinander zu verbinden.

Dieser Aufsatz liefert empirische Belege für die Auswirkungen der Einführung elektronischer Märkte auf die Preise, Preisspitzen und die Preisstreuung eines landwirtschaftlichen Rohstoffs - Tee - in Indien. Es werden hochfrequente monatliche Daten von 2000 bis 2017 verwendet. Um räumliche und zeitliche Korrelationen zu berücksichtigen, wird ein Fixed-Effects-Ansatz mit Standardfehlern nach Driscoll und Kraay verwendet. In Übereinstimmung mit der Theorie deuten die Ergebnisse darauf hin, dass die Einführung elektronischer Märkte die Preise und Preisspitzen bei Tee zwischen 2000 und 2017 um etwa 2% senkte. Darüber hinaus erhöhten elektronische Marktplätze zunächst die Preisstreuung zwischen den Märkten um ca. 11-14%. Im Laufe der Zeit reduzierte sich die Preisstreuung dann aber wieder um 16%.

Der dritte Aufsatz analysiert den Effekt von Mobiltelefonen auf die Arbeit außerhalb der Landwirtschaft. Dieser Aufsatz testet die Hypothese, dass der Besitz eines Mobiltelefons die außerlandwirtschaftliche Arbeit der ländlichen Haushalte erhöht. Für diesen Abschnitt wurden national repräsentative Paneldaten verwendet, die Methoden basieren auf Regressionsmodellen mit festen Haushaltseffekten und einem Instrumentalvariablenansatz. Die Ergebnisse deuten darauf hin, dass der Besitz von Mobiltelefonen die Wahrscheinlichkeit einer Teilnahme an verschiedenen Arten von außerlandwirtschaftlicher Beschäftigung signifikant erhöht, einschließlich Gelegenheitslohnarbeit, abhängiger Beschäftigung und nichtlandwirtschaftlicher Selbständigkeit. Die Auswirkungen von Mobiltelefonen sind für alle Arten von ländlichen Haushalten signifikant, nehmen aber tendenziell mit dem Grad der Abgeschiedenheit zu.

Schließlich wurde der vierte Aufsatz auf der Prämisse aufgebaut, dass in vielen Entwicklungsländern informelle Institutionen (soziale und geschlechtsspezifische Normen), strukturelle Hindernisse (schlechte Qualität von Straßen und Transportsystemen) und Sicherheitsüberlegungen die Mobilität von Frauen oft einschränken. In diesem Kontext, in dem Frauen physisch und wirtschaftlich isoliert sind, versprechen Mobiltelefone ein effektives Instrument zu sein, um sie mit Märkten und Dienstleistungen zu verbinden, indem sie den Zugang zu Informationen verbessern, zwischenmenschliche Netzwerke ermöglichen, einstellungsbezogene Merkmale beeinflussen und die physische Mobilität verbessern. Dieser Aufsatz analysiert die Auswirkungen von Mobiltelefonen auf geschlechtsspezifische Ergebnisse unter Verwendung national repräsentativer Daten aus Indien, die 2011-12 unter Anwendung eines Instrumentalvariablenansatzes erhoben wurden,. Die Ergebnisse legen nahe, dass Mobiltelefone einen positiven und signifikanten Effekt auf die Mobilität von Frauen und den Zugang zu reproduktiv-medizinischen Gesundheitsdiensten haben. Die disaggregierte Analyse deutet darauf hin, dass der Effekt für Frauen aus armen Haushalten höher ist als der von nicht-armen Haushalten. Selbst für Frauen, die in einer relativ konservativen Gemeinschaft leben und zur Zurückgezogenheit verpflichtet sind, haben Mobiltelefone einen signifikanten und positiven Effekt.

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LIST OF ABBREVIATIONS

APL	Above Poverty Line
ATT	Average Treatment Effect on the Treated
BPL	Below Poverty Line
CIA	Conditional Independence Assumption
FE	Fixed Effects
FPO	Farmer Producer Organisation
ICT	Information Communication Technology
IHDS	India Human Development Survey
IPWRA	Inverse Probability Weighted Regression Adjustment
ITU	International Telecommunication Union
IV	Instrumental Variable
IVR	Interactive Voice Response
KBM	Kernel Based Matching
LPM	Linear Probability Model
LSDV	Least Squares Dummy Variable
MIS	Market Information Systems
MP	Mobile Phone
NABARD	National Bank for Agriculture and Rural Development
NAM	National Agricultural Market
NNM	Nearest Neighbour Matching
OBC	Other Backward Class
OLS	Ordinary Least Square
PSM	Propensity Score Matching
RE	Random Effects
RM	Radius Matching
SC	Scheduled Caste
SD	Standard Deviation
SE	Standard Error
SMS	Short Messaging System
ST	Scheduled Tribe
TRAI	Telecom Regulatory Authority of India
USD	United States Dollar
WTP	Willingness to Pay

CHAPTER 1: INTRODUCTION

1.1 PROBLEM STATEMENT

In developing countries, the cost of acquiring information is substantially high because information is either limited, asymmetrically distributed, or unproductively transmitted. The difficulties related to obtaining information have important consequences on how individuals and markets behave in the absence of perfect information (Stiglitz, 1988). Often, information problems result in the inability to undertake mutually beneficial transactions as high search costs prevent buyers and sellers from either finding each other or acquiring enough information to confidently proceed with a transaction (World Bank Group, 2016). Moreover, it may lead to inefficiencies in the allocation of resources (Torero & von Braun, 2006). Thus, high information cost may reduce the extent of market exchange and lead to economy-wide Pareto inefficiencies (Greenwald & Stiglitz, 1986; Stiglitz, 1988). Under these circumstances, a key policy question for promoting rural development and poverty reduction in the context of developing countries is: how information constraints faced by rural households can be overcome? One potential mechanism to reduce information constraints is the use of digital technologies, which build on information and communication technologies (ICTs) such as internet platforms and mobile phones (Deichmann et al., 2016; World Bank Group, 2016). Past literature has highlighted that information and communication technologies (ICTs) have the potential to serve as an important channel of information by providing cost-effective communications (Nakasone et al., 2014; Torero & von Braun, 2006). Over the last few years the use of ICTs has further evolved and new digital technologies—the internet, mobile phones, and other tools to collect, store, analyse, and share information digitally— have emerged (World Bank Group, 2016). This dissertation empirically analyses the implications of three types of digital technologies— personalized digital extension services, electronic marketplaces, and mobile phones— on various development outcomes in India, such as agriculture performance, efficiency in agro-based commodity markets, rural off-farm opportunities, and gender outcomes.

1.1 CONCEPTUAL FRAMEWORK

The approach of this thesis is to consider digital technologies as an instrument to reduce transaction costs by lowering the cost of acquiring and disseminating information. In the context of developing countries, premodern communication facilities and the high cost of transmitting information over time and space frequently limit the number of users of information and also decrease the expected returns from investing in the production of information (Leff, 1984). Under such situations, modern digital technologies have the potential to overcome some of the information barriers that exist in low-income and emerging economies. Leff (1984), Torero & von Braun, (2006), and World Bank Group (2016) highlight that the reduction in information costs can have several effects on individuals, markets, and the economy, such as:

- **Increased supply of information:** The production of information involves high fixed costs but low marginal costs (Stiglitz, 1988). As technological advances are made in areas such as open-source software, artificial intelligence, and machine learning, the operating costs of digital technologies can fall close to zero. A reduction in the cost of transmitting information can increase the supply of information, which in turn will result in a decline in the price of information.

- **Improved quality of information:** In addition to increasing the quantity of information, digital technologies can improve the quality of available information by personalizing the information to the needs of customers by using predictive analytics and machine learning algorithms.

- **Increased access to information and improved decision-making:** The increased availability of information will also shift outward the demand curves for information. Generally, the quantity of information that individuals use in economic decision-making should satisfy the standard marginal conditions. Thus, by lowering information costs, digital technologies make it viable for economic agents to obtain information that is relevant for transactions (Leff, 1984) and lead to more informed and improved decision-making.

- **Market efficiency:** As the cost of acquiring information through digital technologies falls, the amount of search that is privately and socially optimal rises. This can promote increased arbitrage and improve market efficiency (Aker, 2010; Jensen, 2007; Stahl, 1989; Stigler, 1961).

- **Emergence of new markets:** A reduction in the cost of obtaining information and negotiating transactions can facilitate inclusion by creating new markets: expanding trade, access to new input and output markets, increasing employment, and improving access to public services (Torero & von Braun, 2006; World Bank Group, 2016).

- **Institutional changes:** In developing countries, many informal institutions[1] exist due to widespread uncertainty and the high cost of information (Leff, 1984; Stiglitz, 1988). Thus, it is likely that a fall in the information costs due to better communication technologies may facilitate some institutional changes. For instance, women in developing countries experience disproportionally higher costs of information than men. Costly and asymmetric information isolate women economically and socially, thereby affecting the optimal utilization of resources women control, their access to outside options, and exposing them to higher levels of risks (Fletschner & Mesbah, 2011). This can leave women in a weaker or more vulnerable position. In this context, digital technologies can foster institutional changes in the way traditional gender roles are defined by connecting women to markets and services, mobilizing interpersonal networks, influencing attitudinal attributes, and improving physical mobility.

- **Innovations in business models:** The fixed costs of developing a digital platform are usually high, but once the platform is developed, the marginal cost of carrying out an additional transaction or including another user can be at very little cost. This characteristic of emerging digital technologies gives rise to increasing returns to scale, which stimulates new business models (World Bank Group, 2016).

- **Network effects:** As the marginal cost of transacting through digital technologies approaches zero, more sellers/service providers or buyers/consumers are likely to use the digital technology, thereby creating network effects where the benefit to a customer grows as more sellers/service providers are added to the platform and vice versa (Torero & von Braun, 2006).

- **Increased aggregate output:** Digital technologies have the potential to reduce transaction costs in several markets and thereby increase aggregate output in the economy.

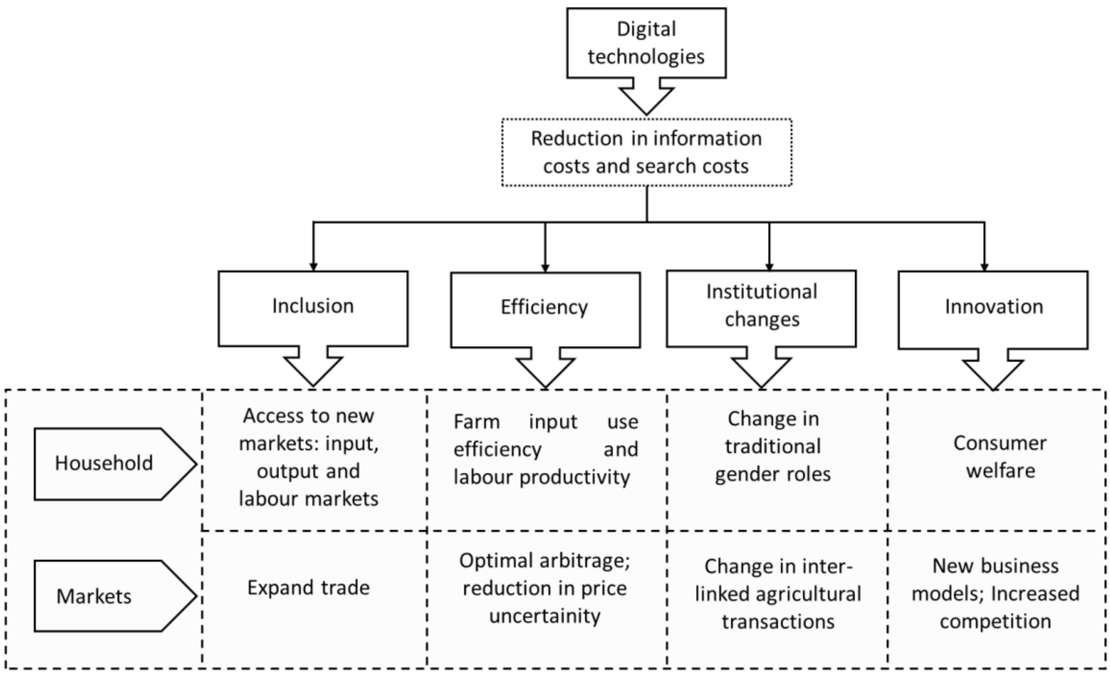
Keeping these possible implications of digital technologies in mind, Figure 1 presents a diagrammatic representation of how digital technologies can result in inclusion, efficiency gains, institutional changes, and innovations. On the farm and homestead, digital technologies can enable informed decision-making, improve access to new input and output markets, and open up new job opportunities. It can also facilitate institutional changes in the way traditional gender roles are defined. Further, in developing countries, informal institutions such as inter-linked product and credit markets or other forms of inter-linked agricultural contractual arrangements, exist due to high transaction costs. Thus, off the farm, digital

[1] Socially shared rules that are communicated and enforced outside formal channels

technologies can enable changes in the way rural households interact in markets. A reduction in search costs can facilitate the participation of more buyers and sellers and increase competition in markets. It can also make markets more efficient by enabling market agents to undertake optimal arbitrage. Moreover, a reduction in the marginal cost of carrying out an additional transaction can result in the expansion of trade and induce innovations in new business models. Using this conceptual framework, this thesis comprises of four essays in which it empirically tests the following hypothesis:

1. Access to personalised digital extension services improves decision-making in farming and enhances agriculture performance.
2. Reducing search costs between buyers and sellers through an internet-enabled electronic marketplace increases competition, makes markets more efficient, and reduces spikes in prices.
3. Reduction in the cost of obtaining employment-related information and the decrease in the cost of negotiation through mobile phones increases rural households' off-farm employment.
4. Access to information and knowledge at low costs through mobile phones improves women's well-being.

Figure 1.1: Conceptual framework



Source: Adapted from World Bank Group (2016)

1.2 A REVIEW OF RELEVANT LITERATURE

There is a growing body of literature highlighting that ICTs can lower the cost of communication significantly, thus reducing transaction costs, increasing market efficiency, and promoting economic growth and poverty reduction (Aker, 2011; Nakasone et al., 2014). Table 1 summarizes some of the published empirical literature on the effects of digital technologies on different aspects of development. One strand of the literature focuses particularly on the role of mobile phones for agricultural development. For instance, several studies evaluated the effects of using mobile phones on agricultural market prices and trader search behaviour (Abebaw & Haile, 2013; Aker & Fafchamps, 2014; Shimamoto et al., 2015; Tack & Aker, 2014), smallholder market access, and participation (Fan and Salas Garcia 2018; Lashitew *et al*. 2019; Muto and Yamano 2009; Pellegrina *et al*. 2017; Tadesse and Bahiigwa 2015; Tchamyou *et al*. 2019; Zanello 2012), farm productivity and income (Abdul-Salam & Phimister, 2017; Aker & Ksoll, 2016; Fu & Akter, 2016; Kiiza & Pederson, 2012; Lio & Liu, 2006) and adoption of technology and access to knowledge (Larochelle et al., 2019; Maredia et al., 2018; Van Campenhout et al., 2017). Some studies analysed the impacts of mobile phones on other dimensions of smallholder welfare, such as nutrition and gender equality (Parlasca et al., 2020; Sekabira & Qaim, 2017b), and migration (Muto, 2012). Most of these studies focus on mobile phones as a simple communication tool. A few other studies looked at the effects of mobile phone-based financial services, such as mobile money on farm performance and household welfare (Jack & Suri, 2011; Kikulwe et al., 2014; Munyegera & Matsumoto, 2016; Sekabira & Qaim, 2017a). Overall, these studies suggest that mobile phones can be very beneficial for rural households.

Further, recent studies have analysed the use of the internet and smartphones in rural areas of developing countries and their effects on household welfare (Hübler and Hartje 2016; Ma *et al*. 2020; Nie *et al*. 2020). Technological advancements in areas such as open-source software, artificial intelligence, and machine learning have contributed to the emergence of new, internet-based platforms that aggregate supply and demand by connecting producers/sellers directly to input and output markets. These new internet-based applications and technologies could have major implications for rural development, however, the literature on how these new digital technologies affect rural households and markets remains relatively thin. Several studies showed that providing farmers with general market and weather information through mobile phones, text messages, or internet applications can promote agricultural productivity and market efficiency (Aker, 2011; Baumüller, 2018; Fafchamps & Minten, 2012; Fu & Akter, 2016; Goyal, 2010; Ogutu et al., 2014). There are also a few studies that analysed the effects of using training videos or call centers and interactive voice response services for farmers, with somewhat mixed results (Aker et al., 2016; Van Campenhout et al., 2021). However, in these examples, ICTs were used primarily to improve the delivery of generic extension information. There is only one published study analysing the effects of personalized advice, namely Arouna et al., (2020) who showed that fertilizer advice tailored to farmers' soil conditions through the use of a mobile application helps to increase crop productivity in Nigeria.

Keeping the existing literature on ICT and digital technologies in mind, the first essay of this dissertation evaluates the impact of a digital tool that reduces information barriers on the input-side of farm production by providing personalised extension services through an agriculture technology platform. The second essay explores the effects of using an electronic marketplace to connect buyers and sellers in the output market. Previous studies that have analysed the effects of online commerce on consumer durable goods such as used cars, books, compact discs, and term life insurance in high-income countries have found mixed evidence on the impact of electronic marketplaces on prices and market efficiency. Few studies have claimed that prices have fallen and markets have become more efficient, while others have claimed that prices are higher and that the electronic marketplaces may not be as efficient as expected (Brown & Goolsbee, 2002; Brynjolfsson & Smith, 2000; Clay et al., 2001; Kiviet, 1999). Since empirical findings are diverse on the implications of electronic commerce, it is essential to study the consequences of electronic marketplaces on other internet markets, especially in the context of emerging economies and commodities with limited shelf-life. Thus, the second essay examines if the introduction of electronic marketplaces can affect the performance of agro-based commodity markets in India by undertaking a case study of the tea value chain.

Besides studying the implications of new digital technologies, the thesis also adds to the existing literature on the implications of mobile phones by examining the effects of mobile phones on rural off-farm employment and gender outcomes. In the context of the effects of mobile phones on labour market outcomes, there is only one study that analyses the impact of mobile phones on rural-urban migration (Muto, 2012). While migration is often driven by labour market opportunities, the third essay explicitly examines the effects of mobile phones on rural off-farm employment and also analyses heterogenous effects of mobile phones on off-farm employment based on geographical location and size of networks. Further, from the gender perspective, there is only one empirical study that has analysed the effects of mobile phones on gender equality (Sekabira & Qaim, 2017b). Therefore, the fourth essay adds to this sparse literature by analysing the consequences of mobile phones on women's physical mobility and access to reproductive healthcare services.

1.3 RESEARCH QUESTIONS

To fill the research gap in the literature of digital technologies, the following research questions are addressed in different chapters of this thesis:

1. Does access to personalized digital extension services affect agriculture performance?
2. Do electronic marketplaces affect the prices and spikes in the prices of tea?
3. What are the effects of the introduction of electronic marketplaces on market efficiency?
4. Can ownership of mobile phones increase rural households' off-farm employment?
5. Does the effect of mobile phones on off-farm employment depend on households' physical remoteness?
6. What are the effects of mobile phones on off-farm employment for households with large informal social networks?
7. Do mobile phones affect women's physical mobility and access to reproductive healthcare services?
8. Does the effect of mobile phones on gender outcomes vary with the economic status of the household and households in which social norms and customs play an important role?

Table 1.1: Empirical literature on the effects of digital technologies

Digital technologies	Outcome variables	Authors
Mobile phone [voice calls, audio-visual messages/ video, interactive voice response (IVR) service, short message services (SMS)]	Price dispersion between markets and sellers	Aker, 2010; Jensen, 2007
	Price asymmetry between traders and farmers	Svensson & Yanagizawa, 2009
	Traders search behaviour	Tack & Aker, 2014
	Farmers bargaining power, selling prices, and price expectations	Haile et al., 2019; Shimamoto et al., 2015
	Smallholder market access and participation	Fan & Salas Garcia, 2018; Lashitew et al., 2019; Muto & Yamano, 2009; Pellegrina et al., 2017; Tadesse & Bahiigwa, 2015; Tchamyou et al., 2019; Zanello, 2012
	Farm productivity, input use, and income	Abdul-Salam & Phimister, 2017; Aker & Ksoll, 2016; Cole & Fernando, 2012; Fu & Akter, 2016; Kiiza & Pederson, 2012; Lio & Liu, 2006; Van Campenhout et al., 2021
	Adoption of technology and access to knowledge	Larochelle et al., 2019; Maredia et al., 2018; Van Campenhout et al., 2017
	Nutrition and gender equality	Parlasca et al., 2020; Sekabira & Qaim, 2017
	Migration	Muto, 2012
	Consumption and poverty	Beuermann et al., 2012
	Small-scale enterprises	Müller-Falcke, 2002
Mobile money	Farm performance and household welfare	Kikulwe et al., 2014; Kirui et al., 2012; Munyegera & Matsumoto, 2016; Sekabira & Qaim, 2017a
	Consumption	Jack & Suri, 2014
Internet, smartphones, and computers	Household welfare	Hübler & Hartje, 2016; Ma et al., 2020; Nie et al., 2020
	Income diversification	Leng et al., 2020
Internet kiosks	Market prices and area under cultivation	Goyal, 2010
ICT based market information system	Farm input use and productivity	Ogutu et al., 2014
Android-based application	Farm productivity and profits	Arouna et al., 2020

1.4 ORGANIZATION OF THE THESIS

In the first essay, research question number one is addressed using primary observational data from India collected in 2019. This chapter analyses the effects of personalized digital extension services on smallholder agricultural performance. Problems of selection bias in the impact evaluation are reduced through propensity score matching combined with estimates of farmers' willingness to pay for digital extension. The second and third research questions are analysed in the second essay using high-frequency monthly cross-sectional time-series data from 2000 to 2017 and applying a fixed-effects approach with Driscoll and Kraay standard errors to deal with spatial and temporal correlation. The second chapter provides empirical evidence on the effects of the introduction of electronic markets on prices, spikes in prices, and price dispersion of an agro-based commodity—tea— in India.

Research questions 4 to 6 are addressed in the third essay. This essay argues that the increasing spread of mobile phones could help improve access to employment-related information at relatively low costs. Using nationally representative panel data from rural India (2004-05 and 2011-12) and regression models with household fixed effects and an instrumental variable approach this chapter tests the hypothesis that ownership of a mobile phone increases rural households' off-farm employment. In addition to the average effects of mobile phones, heterogeneous effects are estimated for households in different locations. Here it is hypothesized that the positive employment effects increase with households' physical remoteness.

Using nationally representative data from India collected in 2011-12 and applying an instrumental variable approach, the fourth essay analyses the seventh and eighth research questions. The approach of the fourth essay is to think of mobile phones as a tool for improving women's bargaining process, and thus, analyse their effects on gender outcomes. In many developing countries informal institutions (social and gender norms), structural impediments (inadequate and poor quality of roads and transport systems), and security considerations often restrict women's mobility. In this context, where women are physically and economically isolated, mobile phones promise to be an effective instrument to connect them to markets and services by improving access to information, mobilizing interpersonal networks, influencing attitudinal attributes, and improving physical mobility. The final chapter summarizes the findings of the thesis and presents policy recommendations.

CHAPTER 2: EFFECTS OF PERSONALIZED DIGITAL EXTENSION SERVICES ON AGRICULTURAL PERFORMANCE: EVIDENCE FROM SMALLHOLDER FARMERS*

ABSTRACT

Productivity growth in smallholder agriculture is an important driver of rural economic development and poverty reduction. However, smallholder farmers often have limited access to information, which can be a serious constraint for increasing productivity and commercialization. One potential mechanism to reduce information constraints is the public agricultural extension service, but its effectiveness has often been low in the past. Digital technologies could enhance the effectiveness of extension by reducing outreach costs and helping to better tailor the information provided to farmers' individual needs and conditions. Using primary data from India, this study analyses the effects of digital extension services on smallholder agricultural performance. The digital extension services that some of the farmers use provide personalized information on the types of crops to grow, the types and quantities of inputs to use, and other methods of cultivation. Problems of selection bias in the impact evaluation are reduced through propensity score matching (PSM) combined with estimates of farmers' willingness to pay for digital extension. Results show that the use of personalized digital extension services significantly increases input intensity, production diversity, crop productivity, and levels of commercialization. Total crop income is increased by 25%.

2.1 INTRODUCTION

In developing countries, productivity growth in small-farm agriculture can serve as an important driver of economic development and poverty reduction (Mellor & Malik, 2017; Ogutu & Qaim, 2019). However, smallholder farmers typically face many

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challenges, such as unpredictable weather conditions, market risks, and limited access to information, technologies, and financial services (Manda et al., 2020). These and other constraints result in low productivity and low rates of market participation (Key et al., 2000) Hence, a key policy question for promoting rural development and poverty reduction is how the main information and market access constraints that smallholder farmers face can be overcome.

In most developing countries, agricultural extension services are the dominant method of public-sector support towards knowledge diffusion and innovation in the small-farm sector (Takahashi et al., 2020). Traditionally, extension agents have either tried to educate farmers directly about best practices or have worked with selected 'model farmers' who are then expected to act as information multipliers (Taylor & Bhasme, 2018). However, the effectiveness of traditional extension approaches has been limited, either because of too little funding and thus low outreach or information that is not sufficiently tailored to farmers' needs (Takahashi et al., 2020; Taylor & Bhasme, 2018). The development and use of new digital extension approaches, which build on information and communication technologies (ICTs) such as mobile phones and internet platforms, could potentially improve the situation, but empirical evidence of actual impacts is scarce. In this article, we use data from smallholder farmers in India to analyse whether digital extension with personalized advice can help to increase innovation, productivity, and income.

There is a growing body of literature highlighting that ICTs can lower the cost of communication significantly, thus reducing transaction costs, increasing market efficiency, and promoting economic growth and poverty reduction (Aker, 2011; Aker & Mbiti, 2010; Jensen, 2007; Kabbiri et al., 2018; Nakasone et al., 2014; Niebel, 2018; Torero & von Braun, 2006). One strand of the literature focuses particularly on the role of mobile phones for agricultural development. For instance, several studies evaluated the effects of using mobile phones on agricultural market prices (Aker & Fafchamps, 2014; Haile et al., 2019; Shimamoto et al., 2015), smallholder market access and participation (Fan and Salas Garcia 2018; Lashitew *et al*. 2019; Muto and Yamano 2009; Pellegrina *et al*. 2017; Tadesse and Bahiigwa 2015; Tchamyou *et al*. 2019; Zanello 2012), and farm productivity and income (Abdul-Salam and Phimister 2017; Aker and Ksoll 2016; Baumüller 2018; Fu and Akter 2016). Some studies analysed the impacts of mobile phones on other dimensions of smallholder welfare, such as nutrition and gender equality (Parlasca et al., 2020; Sekabira & Qaim, 2017b), off-farm employment (Leng *et al*. 2020), and migration (Muto, 2012). Most of these studies focus on mobile phones as a simple communication tool. A few other studies looked at the effects of mobile phone-based financial services, such as mobile money, on farm performance and household welfare (Kikulwe et al., 2014; Sekabira & Qaim, 2017a). Overall, these studies suggest that mobile phones can be very beneficial for smallholder farmers.

Over the last few years – with the rise of high-speed internet connections and web-enabled smartphones – the use of ICTs has further evolved. Recent studies analysed the use of the internet and smartphones in rural areas of developing countries and their effects on household welfare (Hübler and Hartje 2016; Ma *et al*. 2020; Nie *et al*. 2020). Various internet-based applications and technologies are being developed, which could have major implications for agricultural development. Cloud services, low-cost open-source software, and big data analytics contribute to the emergence of new, internet-based 'agricultural technology platforms' (agri-tech platforms henceforth) that aggregate supply and demand by reducing the number of intermediaries and connecting farmers directly to agro-advisory services, input providers, retailers, or consumers (Omulo & Kumeh, 2020; Rao et al., 2017). Rao *et al*. (2017) reviewed such agri-tech platforms in India and categorized them into those that connect farmers to (i) extension and agro-advisory services, (ii) input suppliers, and (iii) buyers of agricultural produce. Similar platforms are also emerging in many other developing countries.

While various types of ICTs are increasingly used in agricultural extension, the literature on how these new digital extension services affect smallholder performance remains relatively thin. Several studies showed that providing farmers with general market and weather information through mobile phones, text messages, or internet applications can promote agricultural productivity and market efficiency (Aker, 2011; Baumüller, 2018; Fafchamps & Minten, 2012; Fu & Akter, 2016; Goyal, 2010; Ogutu et al., 2014). There are also a few studies that analysed the effects of using training videos or call centres and interactive voice response services for farmers, with somewhat mixed results (Aker et al., 2016; Van Campenhout et al., 2021). However, in these examples, ICTs were used primarily to improve the delivery of generic extension information. We are aware of only one published study analysing the effects of personalized advice, namely Arouna et al., (2020) who showed that fertilizer advice tailored to farmers' soil conditions through the use of a mobile application helps to increase crop productivity in Nigeria. We contribute to this literature by evaluating the impact of an agri-tech platform with personalized advice to smallholder farmers in India.

Digital technologies can help to better tailor the information provided to farmers' individual needs and conditions in multiple ways. For instance, predictive analytics and machine learning algorithms can be used to combine data on weather forecasts, soil conditions, market prices, and other aspects to develop and deliver site-specific agricultural recommendations. Theoretically, such digital extension services can affect smallholder households through several mechanisms. First, they can reduce information barriers by providing personalized advice on which types of crops to grow in what season, the appropriate types and quantities of inputs to use, and the best timing for the different operations and input applications. Second, they can connect farmers to new input markets by providing transparent information on local market prices and reputed brands and suppliers. Third, they can help improve farmers' bargaining power by providing transparency and additional supplier options. Fourth, improved access to personalized information and new technologies and inputs can increase the levels of commercialization. These mechanisms will likely change farmers' cropping patterns and increase their input intensities, crop yields, sales volumes, and incomes.

In this study, we use the example of concrete digital extension services that were recently started in India to analyse whether such positive effects can be observed. For the study, a survey of smallholder farmers was conducted in early 2019. Some of the farmers surveyed already adopted the digital extension services, while others did not. The rest of this article is organized as follows. Section 2.2 explains the survey region in India and the concrete features of the digital extension services, followed by an explanation of the sampling strategy and Section 2.3 describes the outcome variables. Section 2.4 discusses the econometric strategy for the impact evaluation. Section 2.5 presents and discusses the results, while Section 2.6 concludes.

2.2 STUDY REGION AND DATA COLLECTION

2.2.1 Study region

We focus on one large Farmer Producer Organisation (FPO) named 'Mayurbhanj Agri Smart Farmer Producer Company Limited' in Mayurbhanj District in the state of Odisha, eastern India. The FPO comprises around 1000 farmers growing vegetables, rice, and a few other crops. It was initiated in 2017 by the National Bank for Agriculture and Rural Development (NABARD), a public financial institution, and eKutir, a social business enterprise. eKutir also developed the digital agri-tech platform 'Farmex' (*https://farm-ex.io/*) which is of particular interest here. At the time of our data collection in 2019, the agri-tech platform was called 'Farmex'. The name was changed to 'Farmex' in 2021.

Farmex offers farmers real-time agricultural extension services and a marketplace for seeds, fertilizers, and pesticides. In the future, the digital services shall be extended to the output market as well, but when we collected the data in early 2019 this was not yet the case. As part of the extension services, Farmex helps its users to plan season-wise cropping activities and provides information on best practices for growing specific crops. The platform also offers recommendations on the types and quantities of inputs to use and on relevant pests and diseases and how to control them. Moreover, to reduce issues with the use of counterfeit inputs, which are widespread in India, the platform makes suggestions on specific input brands and suppliers.

Due to low levels of education and widespread digital illiteracy among the FPO members, farmers do not receive the extension services on their mobile phones. Instead, when farmers want to adopt the digital extension services, they get in touch with the head of the FPO who then operates the internet-based application on the farmer's behalf. In other words, the FPO head takes on the role of an extension agent, equipped with the digital technology that enables him/her to provide tailor-made agricultural advice and services to the FPO members. Adoption of digital extension services is voluntary for farmers and is currently free of charge. If a member of the FPO decides to adopt the services, the FPO head creates an individual account by entering personalized data, including farm-specific details such as location, land size, types of crops currently grown, and soil conditions. These details – together with the application's algorithms on weather forecasts, market conditions, and optimal production decisions – are processed to provide personalized advice on crop selection, the schedule of agricultural activities, and input regimes. After every season, the FPO head enters additional data on the actual inputs used by each farmer, the yields obtained, and the prices to further improve the algorithms' predictions and advice for future seasons.

2.2.2 Sampling strategy and data collection

Data for this study were collected through a survey conducted between January and March 2019. The selected FPO in Odisha has members in two blocks (Betnoti and

Badasahi) and 26 villages. Out of all 26 villages, we randomly selected 20 villages (10 in each of the two blocks) for data collection (the remaining six villages were used for pre-testing the questionnaire). In each of the sampled villages, a household census was conducted, and all households were categorized into three groups (i) FPO vegetable farmers, (ii) non-FPO vegetable farmers, and (iii) non-FPO non-vegetable farmers. For this study, we were only interested in vegetable farmers because the digital extension services are mainly related to vegetable cultivation. Hence, we only selected farmers from the first two groups on a random basis. The total sample includes 1105 vegetable-growing households, out of which 603 were members of the FPO and 502 were not. This distribution is proportional to the actual population proportions (Table A.1 in the Appendix).

The digital extension services are accessible only to FPO members. However, as adoption for FPO members is voluntary, not all FPO members adopted the digital extension services. Of the 603 FPO members in our sample, around 77% (465) adopted digital extension services, the others did not although they would have been eligible. For our evaluation of the effects on agricultural performance, we only include those farmers that adopted digital extension services as part of the "treatment" group. Hence, the control group includes 640 farm households that did not adopt digital extension services irrespective of their FPO membership. It is important to mention that – beyond the digital agri-tech platform – none of the farmers in the sample villages had access to other types of formal extension services.

Relevant questions with our sampling strategy are why many of the vegetable farmers in the target villages were not members of the FPO and whether it is appropriate to include these non-members in the control group. In this context, it is important to stress that the FPO in Odisha is open to all farmers in the respective villages who grow vegetables, meaning that there are no eligibility criteria in terms of farm size or other factors. Farmers decide themselves whether they want to become FPO member. From the existing literature on farmer organisations we know that farmers' membership decisions typically depend on expected costs and benefits, which are influenced by various socioeconomic characteristics (Fischer & Qaim, 2014). However, as explained above, the FPO in Odisha was only initiated in 2017 (less than two years before the survey), so that many farmers were still considering joining. Table A.2 in Appendix A compares various socioeconomic characteristics between FPO members and non-members in the control group, showing that both types of farms are similar. Hence, pooling FPO members and non-members in the control group seems justified. The existing farmer heterogeneity is addressed with econometric techniques, as is explained further below.

Data from each randomly selected farm household were collected through personal interviews with the person responsible for farm management (mostly the household head) using a structured questionnaire. The interviews were conducted in the local language (Oriya) by trained enumerators who were supervised by the researchers. Before the actual survey, the questionnaire was pretested and adjusted by interviewing 60 households in the six non-sampled villages in the FPO area.

All agricultural data were collected for the 12 months from March 2018 to February 2019 to capture all seasons of the year. Details on crop production were asked separately for the Kharif, Rabi, and Zaid seasons. These seasonal data were summed up later on to calculate annual input and output variables. In addition to the agricultural data, information on various household characteristics, other economic activities, perceptions about digital technologies, and social networks were gathered. These data are used to control for possible confounding factors in the impact analysis.

2.3 OUTCOME VARIABLES

We want to analyse the effects of using digital extension services on agricultural performance. Agricultural performance is measured in terms of crop production diversity, input use intensity, crop productivity, crop commercialization, and crop income. These variables are defined more specifically in the following.

(i) **Crop production diversity:** Farmers in the study area traditionally grow rice and sometimes vegetables. One of the stated objectives of the digital agri-tech platform and extension services is to help farmers diversify their production by growing more types of vegetables for home consumption and market sales. We measure crop production diversity by counting the number of different crop species grown on the farm during the one year before the survey. The effect of the digital extension services on production diversity could be positive if farmers learn about growing new types of vegetables, but it could also be negative if they specialize in particularly lucrative species.

(ii) **Input use intensity:** Input use intensity is measured in terms of the monetary expenditures for seeds, fertilizer, pesticides, and all inputs combined per acre of cropland. Input use intensity is of interest because the digital extension services provide specific advice on the types and quantity of inputs to use. Effects could be positive if farmers previously under-invested in inputs, but they could also be negative if farmers previously overused certain inputs or paid too high prices due to information asymmetry.

(iii) **Crop productivity:** Productivity is measured in terms of the monetary value of the output produced per acre of land, whereby the total land cultivated by the farm is considered. We use monetary values because farmers grow many different types of crops for which physical weights are not easily comparable. Improved access to information through digital extension services is expected to result in higher crop productivity.

(iv) **Crop commercialization:** Crop commercialization is defined here as the share of total crop output sold during the one year before the survey. Many farmers keep some of their output for home consumption. We use average market prices for the particular crops produced to value home-consumed quantities. As the digital extension services are expected to increase productivity and also provide better access to market information, the effect on crop commercialization is also expected to be positive. As the extension provided only refers to crops, we focus on crop commercialization alone and do not include the livestock sector.

(v) **Crop income**: Annual crop income is calculated as the gross value of crop production (including the output not sold valued at average market prices) minus variable production costs (purchased seeds, fertilizer, pesticides, manure, hired labour, irrigation water, machinery, and transportation). It is expected that higher productivity and higher levels of commercialization will also lead to higher crop income.

2.4 ECONOMETRIC APPROACH

2.4.1 MODELLING THE ADOPTION OF DIGITAL EXTENSION SERVICES

Let the decision to adopt digital extension services be a dichotomous choice, such that $D_i = 1$ if household i adopts the digital extension services and $D_i = 0$ otherwise.

Smallholders choose to adopt when the expected utility from using the services (U_{iD}) is greater than the utility from not using them (U_{iN}), such that $U_{iD} > U_{iN}$. The difference between the utility achieved from adopting and not adopting can be denoted by a latent variable Z^*, such that $Z^* = [(U_{iD}) - (U_{iN})] > 0$. Since Z^* is a latent variable, it is unobservable (Cameron & Trivedi, 2005). However, it can be expressed in terms of observed variables as follows:

$$Z_i^* = \beta X_i + \varepsilon_i \,, \quad D_i = 1\,[Z_i^* > 0] \tag{1}$$

where β is a vector of parameters to be estimated, X_i is a vector of household, farm, and contextual characteristics, and ε_i is an error term that is assumed to be normally distributed.

The probability of households adopting the digital extension services can be expressed as:

$$\Pr(D_i = 1|X_i) = Pr(Z_i^* > 0) = \Pr(\beta X_i + \varepsilon_i > 0) = \Pr\,(-\varepsilon_i < \beta X_i) = F(\beta X_i) \tag{2}$$

where F is the cumulative distribution function of $-\varepsilon_i$ (Cameron & Trivedi, 2005). Depending on the assumptions regarding the functional form of F, probit or logit models can be used to model the determinants of digital service adoption.

2.4.2 MODELLING IMPACT

As explained, using digital extension services is expected to affect input use intensity, crop productivity, and income. Similar to Becerril and Abdulai (2010) and Ogutu *et al.* (2014), we link the adoption decision to the outcome variables by considering a simple model where a risk-neutral farmer maximizes income subject to a competitive output and input market and a single production function $Q(W, X)$ that is continuous, strictly increasing, and strictly quasi-concave in a vector of variable inputs W and farm and household characteristics X. The household's income function can be represented as:

$$\max\ Y = \mathrm{PQ}(W, X) - I\,W, \quad \textit{subject to}\ \ Q(W, X) \geq Q \tag{3}$$

where Y is crop income, P is the output market price, and Q is the expected crop output quantity. I is a column vector of input prices, and W is a vector of input quantities. Further, the crop income function can also be expressed as a function of adopting digital extension services D, as well as market output and input prices and farm and household characteristics:

$$Y = f(D, I, P, X) \tag{4}$$

Thus, equation (3) can be rewritten as:

$$max\ Y(D, I, P, X) = PQ(W, X) - IW, \quad subject\ to\ \ Q(W, X) \geq Q \tag{5}$$

Now, applying Hotelling's lemma with respect to input and output prices, output supply and input demand can be obtained by simple differentiation, such that:

$$\frac{dY}{dI} = -W = W(D, I, P, X) \tag{6}$$

$$\frac{dY}{dP} = Q = Q(D, I, P, X) \tag{7}$$

From equations (6) and (7), it can be observed that a farm household's demand for inputs and the levels of crop output and income is influenced by the decision to adopt digital extension services, input, and output prices, as well as farm and household characteristics.

A common approach to estimate these relationships and the effect of digital extension services would be a set of regression models of the following type:

$$L_i = \alpha_o + \alpha_1 D_i + \alpha_2 X_i + \alpha_3 C + \mu_i \tag{8}$$

where L_i is the outcome variable of interest, C is a vector of relevant controls, including input and output prices, and μ_i is a random error term. To evaluate the effects of digital extension services on the outcome, the coefficient α_1 is of particular interest. However, estimating equation (8) will likely generate biased estimates of α_1 because farmers self-selected into adopting digital extension services, which may mean that D_i is correlated with the error term. As an alternative, we use propensity score matching (PSM) combined with several robustness checks. Further details are explained below.

2.4.3 PROPENSITY SCORE MATCHING APPROACH

A propensity score is the conditional probability of assignment to a particular treatment –adoption of digital extension services in our case – given a vector of observed covariates (Rosenbaum and Rubin 1985). It can be specified as:

$$p(X) = \Pr[D = 1|X] = E[D|X]$$

$$p(X) = F\{h(X_i)\} \tag{9}$$

where F{.} is a normal or logistic cumulative distribution function and X is a vector of observed covariates (Becerril & Abdulai, 2010).

The PSM method builds on two assumptions, namely the conditional independence assumption (CIA), which requires that outcome variables be independent of treatment conditional on the propensity score (Caliendo & Kopeinig, 2008), and the presence of common support, which requires that treatment participants have comparable participants in the control group in terms of their propensity scores (Guo and Fraser 2015). If these two conditions hold, the PSM estimator for the average treatment effect on the treated (ATT) can be specified as the mean difference in the outcome variable L over the common support, weighting the comparison units by the propensity score distribution of the participants as follows (Khandker et al., 2010):

$$ATT = E[L_{i1} - L_{i0}|D = 1]$$

$$ATT = E\{E[L_{i1} - L_{i0}|D_i = 1 , p(X)]\}$$

$$ATT = E_{p(X)|D=1}\{E[L_{i1}|D_i = 1, p(X)] - E\ [L_{i0}|D_i = 0, p(X)]\}$$

where L_{i1} denotes the outcome of households adopting and L_{i0} the outcome of households not adopting digital extension services.

Successful matching first requires choosing a set of covariates that satisfy CIA, as omitting important variables can lead to biased estimates (Dehejia & Wahba, 1999). We use a logit regression with a large number of covariates chosen based on economic theory and past literature to estimate the propensity scores of treatment and control group participants.

Nevertheless, it is still possible that unobserved factors such as personal motivation, risk preferences, or entrepreneurial skills affect treatment assignments such that CIA would not hold. To reduce the risk of biased estimates due to relevant unobserved factors, we use an approach similar to Meemken and Qaim (2018). In particular, as part of the survey, we conducted a hypothetical bidding game to elicit respondent's willingness to pay (WTP) for an agri-tech platform that provides digital extension and improved access to input and output markets. After explaining the functioning of such an agri-tech platform, respondents were asked to quote the maximum price they would be willing to pay for a service that enables them to receive crop-related advisory information, order inputs that get delivered to their village, and find buyers for their output using a mobile application. The stated WTP is likely correlated with farmers' motivation, preferences, and entrepreneurial skills, so that it may be a good proxy of relevant unobserved characteristics (Meemken and Qaim 2018; Verhofstadt and Maertens 2014). Hence, including the WTP values as an additional covariate when estimating the propensity scores can help to reduce potential issues of unobserved heterogeneity.

After estimating the propensity scores, we match treatment and control group farmers using three different matching algorithms, namely nearest neighbour matching (NNM), radius matching (RM), and kernel-based matching (KBM). Using and comparing different matching algorithms is common as a robustness check. In nearest neighbour matching, each treated individual is matched with the three closest control group individuals in terms of their propensity scores. Here, matching is done with replacement, meaning that each control group individual can be used more than once as a match. For RM, a tolerance level on the maximum propensity score distance (caliper) is imposed. Here, the size of the caliper is defined as 0.25 of the standard deviation of the logit of the propensity score, as suggested by Rosenbaum and Rubin (1985). KBM is a non-parametric matching estimator that uses weighted averages of all individuals in the control group to construct the counterfactual outcome (Caliendo & Kopeinig, 2008; Guo & Fraser, 2015). After matching treatment and control group individuals based on their propensity scores, the ATT is calculated, as explained above.

Recent research indicated that using propensity scores for matching may lead to biased impact estimates in some situations (King & Nielsen, 2019). To reduce the likelihood of bias, we use two alternative methods as robustness checks. First, we re-estimate all ATTs using inverse-probability weighted regression adjustment (IPWRA)

(Wooldridge, 2007). Second, we estimate the regression models in equation (8) using ordinary least squares (OLS) and including WTP as an additional regressor. As explained, our WTP variable is likely correlated with relevant unobserved characteristics, so that including WTP can reduce issues of unobserved heterogeneity. This approach has become popular in recent impact studies, especially in situations where valid instruments are hard to identify (Bellemare & Novak, 2017; Ruml & Qaim, 2021).

2.5 RESULTS AND DISCUSSION

1.1.1 DESCRIPTIVE STATISTICS

Our analysis is carried out with a total of 1028 farm household observations for which complete data for all relevant variables are available. Descriptive statistics of all outcome and explanatory variables for the sample are presented in Table A.3 in Appendix A. The average age of the household head is 51 years. The average educational level is around 7 years of schooling. The majority of the households are headed by a male; only 7% are headed by a female. Around 82% of the households belong to socially disadvantaged groups, including Scheduled Castes (SC), Scheduled Tribes (ST), and Other Backward Classes (OBC).[2]

In terms of farm sizes, the average household owns around 1.3 acres of land, even though the operational holding is larger by about 4.7 acres. In other words, many households lease in land from other landowners. Based on the operational land holding, 63% of the sample farmers are classified as marginal (<2.5 acres) or small (2.5-5 acres), and 37% are classified as medium (5-10 acres) or large (>10 acres). Around 50% of the cropped area is irrigated. On average, households grow 7 different crop species. In terms of commercialization levels, households sell around 43% of their crop output and travel about 5 km on average to the closest input and output markets. Table A.3 in Appendix A also shows that 43% of the sample households had adopted digital extension services at the time of the survey, while 57% had not. Table 2.1 shows the different types of information that digital extension adopters used.

[2] SC, ST, and OBC are among the most disadvantaged socioeconomic groups in India, recognized as needing special policy attention by the Indian Government. As is common in empirical analysis with micro-level data from India, we use binary variables for these groups to account for differences in socioeconomic status (Krishna *et al.* 2019).

Table 2.1: Types of information used by digital extension service adopters

Type of information used	Percentage of adopters
Types of crops to grow	88%
Methods of cultivating selected crops	88%
Types of inputs to use	85%
Quantity of inputs to use	62%
Where to sell output	17%
Price to sell outputs	5%

Table 2.2 presents descriptive statistics, disaggregated by digital extension service adopters and non-adopters. For many of the variables, we see significant differences between the two groups. On average, adopting households are larger and have older heads that are more likely to be male and are better educated than non-adopting households. Adopters of digital extension services also cultivate more land, have more diversified cropping patterns, and are more commercialized than non-adopters. Finally, adopters of digital extension services have higher crop incomes than non-adopters. These differences may – to some extent – be an effect of adopting digital extension services but may also simply reflect systematic differences between the two groups that existed even before the digital extension services were introduced. We will analyse the effects of digital extension services econometrically below, controlling for possible confounding factors.

Table 2.2: Socioeconomic characteristics of adopters and non-adopters

	Adopters		Non-adopters			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**SE**
Age of household head (years)	51.53	11.67	49.73	14.51	1.81**	(0.84)
Male household head (dummy)	0.96	0.20	0.92	0.27	0.04**	(0.02)
Household head owns a mobile phone (dummy)	0.76	0.43	0.70	0.46	0.06**	(0.03)
Illiterate: highest education of adult male (dummy)	0.05	0.23	0.10	0.29	-0.04**	(0.02)
Primary school: highest education of adult male (dummy)	0.21	0.41	0.27	0.45	-0.06**	(0.03)
Secondary school: highest education of adult male (dummy)	0.44	0.50	0.41	0.49	0.02	(0.03)
Bachelor or Masters: highest education of adult male (dummy)	0.29	0.46	0.19	0.39	0.11***	(0.03)
Scheduled tribe (dummy)	0.12	0.32	0.17	0.38	-0.05**	(0.02)
Scheduled caste (dummy)	0.12	0.32	0.21	0.41	-0.09***	(0.02)
Other backward classes (dummy)	0.56	0.50	0.44	0.50	0.12***	(0.03)
General caste (dummy)	0.21	0.41	0.18	0.38	0.03	(0.02)
Household size (number)	3.89	1.40	3.64	1.45	0.25***	(0.09)
Operated land (acres)	5.53	3.98	4.21	3.99	1.32***	(0.25)
Irrigation ratio (%)	53.98	35.75	48.49	38.56	5.49**	(2.36)
Livestock ownership (livestock units)	1.45	1.41	1.07	0.95	0.38***	(0.07)
Average distance to input and output market (km)	5.68	3.95	4.54	4.14	1.14***	(0.26)
Willingness to pay for digital agri-tech platform services (Rupees)	256.79	423.26	192.19	374.31	64.61***	(24.96)
Peer group [a]	13.91	8.47	11.61	9.75	2.30***	(0.58)
Off farm income (dummy)	0.60	0.49	0.69	0.46	-0.09***	(0.03)
Outcome variables						
Number of crops grown	8.45	4.83	6.35	4.41	2.10***	(0.29)
Seed expenditure (1,000 Rupees/acre) [b]	0.79	0.86	0.73	0.98	0.060	(0.06)
Fertilizer expenditure (1,000 Rupees/acre) [b]	1.80	1.35	1.73	1.62	0.07	(0.09)
Pesticides expenditure (1,000 Rupees/acre) [b]	0.69	0.73	0.65	0.95	0.03	(0.054)
Input expenditure (1,000 Rupees/acre) [b]	3.27	2.53	3.11	3.17	1.67	(1.83)
Crop productivity (1,000 Rs/acre) [b]	16.03	18.78	14.41	14.10	16.22	(1.02)
Commercialization (share of farm output sold 0-1)	0.51	0.28	0.38	0.33	0.13***	(0.02)
Crop income (1,000 Rs/acre) [b]	46.89	83.37	27.12	48.76	19.77***	(4.15)
Observations	440		588		1028	

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. [a] Number of households within the village from the same caste who adopted digital extension services. [b] These monetary variables are used in logarithmic form in the regression models.

2.5.1 FACTORS INFLUENCING THE ADOPTION OF DIGITAL EXTENSION SERVICES

Results of the logit model to explain the factors influencing digital extension service adoption are shown in Table 2.3. Age, education, size of the land operated, asset ownership, and several other farm and household characteristics have a positive influence on the decision to adopt digital extension services.[3] The age of the household head and size of the land operated have a non-linear influence on adoption. As the age of the household head increases, initially, there is a positive effect, but this positive effect becomes smaller with further increasing age. Similarly, as the size of the land operated increases, at first, there is a positive effect on digital extension service adoption, but this positive effect gets smaller with further increasing land size. The turning points for age and the size of the land operated are 45.7 years and 11.6 acres, respectively.

The WTP variable, which proxies for unobserved factors such as motivation, preferences, and entrepreneurial skills, is also positively associated with the adoption of digital extension services, as one would expect. Further, the size of the social network has a positive effect: a larger number of people who adopted digital extension services from the same caste and living in the same village as the respondent is associated with a higher probability of individual adoption.

In contrast, having off-farm income negatively influences the decision to adopt digital extension services (Table 2.3), probably because households pursuing off-farm income concentrate less on improving their farming business than households for whom agriculture is the only source of income. Off-farm income can have positive effects on farm investments, especially when access to agricultural credit is constrained (Haggblade *et al*. 2007). However, the off-farm economy can be very diverse. For many farmers with very small landholdings, pursuing off-farm economic activities is often a simple survival mechanism rather than a conscious strategy to accumulate capital for farm upgrading (Davis *et al*. 2009).

In the logit model, we also control for distance to input and output markets. Market distance may be less relevant for the adoption of digital extension services that are

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[3] We use education and mobile phone ownership as proxies for digital literacy. Measuring digital literacy more directly with one variable or index is not straightforward, apart from the fact that such a variable in our context might possibly be associated with reverse causality issues.

offered in the local context, but may certainly influence several of our outcome variables – such as input use and crop productivity – through various channels. Hence, it is important to control for general market access when calculating the propensity scores.

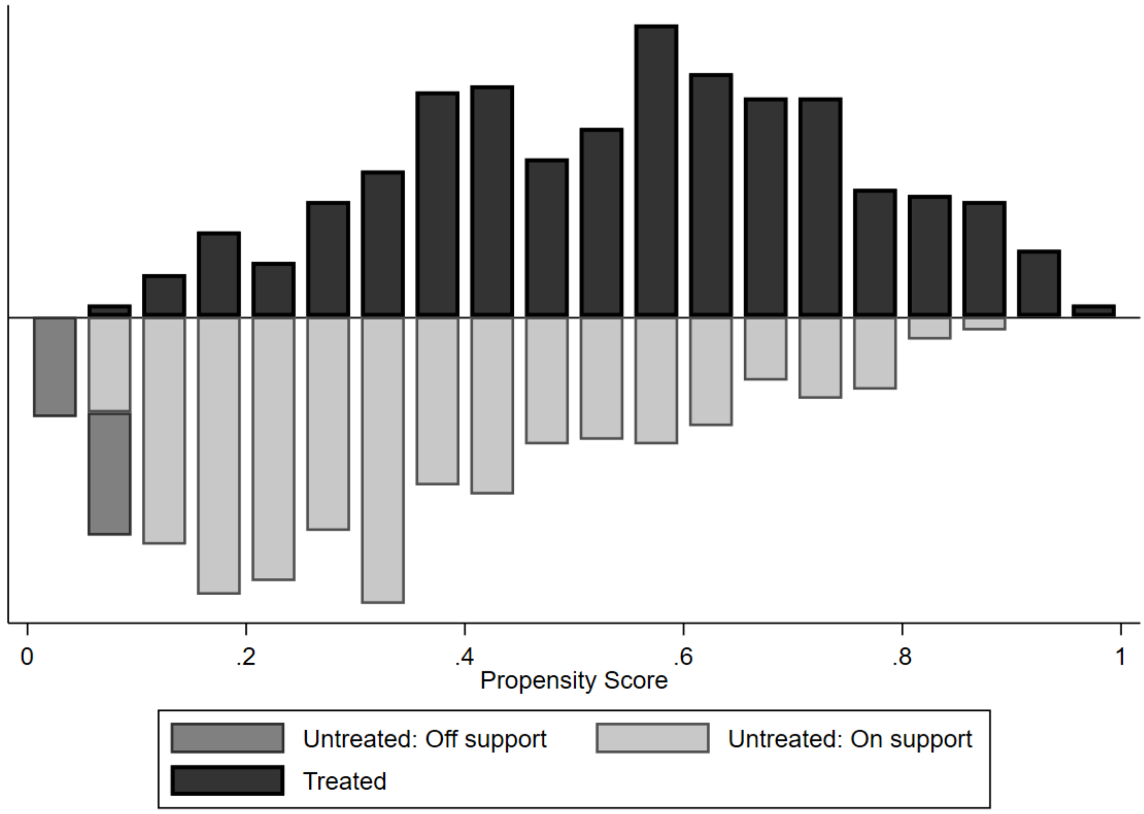
Table 2.3: Logit estimates of the propensity to adopt digital extension services

	Coefficient	Robust SE
Age of household head (years)	0.183***	(0.038)
Age squared	-0.002***	(0.000)
Male household head (dummy)	0.384	(0.329)
Household head owns a mobile phone (dummy)	0.332*	(0.191)
Primary school (dummy)	0.492*	(0.295)
Secondary school (dummy)	0.604**	(0.275)
Bachelor or Masters (dummy)	0.748**	(0.298)
Scheduled tribe (dummy)	-0.350	(0.288)
Scheduled caste (dummy)	-0.366	(0.302)
Other backward classes (dummy)	-0.189	(0.234)
Household size (number)	0.095*	(0.053)
Operated land (acres)	0.139***	(0.051)
Square of operated land (acres)	-0.006**	(0.003)
Irrigation ratio (%)	0.001	(0.002)
Livestock ownership (livestock units)	0.185**	(0.076)
Distance to input and output market (km)	0.028	(0.021)
WTP for digital agri-tech platform services (log)	0.295***	(0.093)
Peer group	0.031**	(0.013)
Off farm income (dummy)	-0.444***	(0.162)
Constant	-8.912***	(1.283)
Village dummies	Yes	
Observations	1028	
Log-likelihood	-580.957	
Pseudo R^2	0.172	
p-value	0.0000	

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. Robust standard errors in parentheses.

Based on these logit estimates, we calculated the propensity scores for matching treatment group households that adopted digital extension services and control group households that did not adopt. Figure 2.1 presents the distribution of propensity scores and the region of overlap and common support. As can be seen, there is a substantial overlap of the propensity scores of both groups, meaning that the assumption of common support, which is necessary for efficient PSM, is satisfied.

Figure 2.1: Distribution of estimated propensity scores and region of common support



2.5.2 COVARIATE BALANCING TESTS

Table 2.4 presents results of the covariate balancing tests to assess how well the propensity score matching performed, or, in other words, whether digital extension service adopters and non-adopters are comparable in terms of observed covariates. For the balancing tests, we calculated mean covariate differences and conducted independent sample *t*-tests before and after matching. A match is considered successful when all *t*-tests result in non-significant differences between the treatment and the control group after matching. The results in Table 2.4 confirm that successful matching is achieved with all three matching algorithms.

Another way of testing covariate balancing is through the standardized mean bias before and after matching. These results are presented in the lower part of Table 2.4. As can be seen, significant mean bias reduction is achieved with all three matching algorithms. A third diagnostic test is a comparison of the pseudo-R^2 from the logit model before and after matching, which is also shown in the lower part of Table 2.4.

For all three matching algorithms, the pseudo-R^2 after matching is low, suggesting that the systematic differences in the covariates that existed before matching were successfully removed.

Table 2.4: Covariate balancing tests

	Nearest neighbour matching			Radius matching			Kernel matching		
Covariates	**% Bias reduction**	***p*-value mean difference, unmatched**	***p*-value mean difference, matched**	**% Bias reduction**	***p*-value mean difference, unmatched**	***p*-value mean difference, matched**	**% Bias reduction**	***p*-value mean difference, unmatched**	***p*-value mean difference in, matched**
Age of household head	82.2	0.035	0.727	78.0	0.035	0.633	77.1	0.035	0.621
Age squared	82.8	0.226	0.848	54.7	0.226	0.576	54.9	0.226	0.578
Male household head	82.1	0.000	0.434	96.2	0.000	0.875	99.5	0.000	0.983
Household head owns a mobile phone	69.0	0.007	0.481	86.5	0.007	0.731	90.7	0.007	0.813
Primary school	28.2	0.016	0.160	93.9	0.016	0.891	90.1	0.016	0.825
Secondary school	89.3	0.198	0.915	88.1	0.198	0.893	84.5	0.198	0.861
Bachelor or Master	66.9	0.000	0.355	88.8	0.000	0.721	82.8	0.000	0.580
Scheduled tribe	100.0	0.002	1.000	90.6	0.002	0.750	92.6	0.002	0.801
Scheduled caste	70.0	0.000	0.290	88.7	0.000	0.644	86.7	0.000	0.588
Other backward classes	89.4	0.000	0.710	99.8	0.000	0.994	97.2	0.000	0.912
Household size	66.7	0.001	0.421	93.2	0.001	0.849	89.4	0.001	0.765
Operated land	71.3	0.000	0.188	97.8	0.000	0.910	94.5	0.000	0.775
Square of operated land	35.3	0.005	0.135	90.1	0.005	0.791	86.4	0.005	0.717
Irrigation ratio	63.0	0.021	0.483	80.9	0.021	0.686	76.0	0.021	0.612
Livestock ownership	72.5	0.000	0.180	90.5	0.000	0.588	94.8	0.000	0.767
Distance to input and output market	69.3	0.000	0.281	96.8	0.000	0.899	89.9	0.000	0.686
WTP (log)	67.2	0.000	0.128	94.6	0.000	0.767	89.6	0.000	0.569
Peer group	85.3	0.000	0.603	84.6	0.000	0.528	88.8	0.000	0.646
Off-farm income	44.3	0.002	0.202	96.0	0.002	0.915	98.5	0.002	0.967
Mean bias before matching		16.7			16.7			16.7	
Mean bias after matching		5.3			2.2			2.5	
p-value of LRChi² unmatched		0.000			0.000			0.000	
p-value of LRChi² matched		0.954			1.000			1.000	
Pseudo-R² unmatched		0.174			0.174			0.174	
Pseudo-R² matched		0.027			0.005			0.006	

2.5.3 IMPACT OF ADOPTING DIGITAL EXTENSION SERVICES

Table 2.5 presents the PSM treatment effects of adopting digital extension services on agricultural performance. All three matching estimators indicate that adopting digital extension services has positive effects on all indicators of agricultural performance.

After controlling for confounding factors, the digital extension services increase production diversity by around one additional crop species grown on the farm. The digital information enables farmers to cultivate additional crops that they have not grown before. The monetary outcome variables are log-transformed, so the respective ATTs can be interpreted in percentage terms. The results in Table 2.5 suggest that the digital services increase input intensity by 15-20%. Crop productivity is increased by around 18%, whereas the degree of crop commercialization is up by 5-7 percentage points. Finally, Table 2.5 reveals that using digital extension services increases crop income by 25-29%.

Table 2.5: Impact of adopting digital extension services on agricultural performance (PSM results)

	Nearest neighbour matching		**Radius matching**		**Kernel matching**	
Outcome variable	**ATT**	**SE**	**ATT**	**SE**	**ATT**	**SE**
Number of crops grown	1.211***	(0.443)	1.017***	(0.371)	1.095***	(0.355)
Seed expenditure per acre (log)	0.170	(0.115)	0.200**	(0.099)	0.198**	(0.097)
Fertilizer expenditure per acre (log)	0.161**	(0.077)	0.149**	(0.062)	0.153**	(0.064)
Pesticide expenditure per acre (log)	0.199**	(0.102)	0.195**	(0.086)	0.198**	(0.083)
Total expenditure per acre (log)	0.188**	(0.079)	0.194***	(0.066)	0.197***	(0.066)
Crop productivity (log)	0.175**	(0.065)	0.175***	(0.059)	0.177***	(0.058)
Crop commercialization	0.074***	(0.028)	0.049**	(0.024)	0.049**	(0.023)
Crop income (log)	0.285**	(0.132)	0.254**	(0.107)	0.265**	(0.107)

ATT: average treatment effect on the treated. PSM: propensity score matching. Bootstrapped standard errors with 1000 replications are shown in parentheses. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level

Based on these estimates, we conclude that digital technologies that use data from farms to provide personalized information are effective in terms of helping farmers to make better cropping, technology, and input decisions. The information provided by the digital extension services on the best types of crops to grow, the appropriate methods of cultivation, the optimal timing of the different operations, and the suitable input regimes help farmers to allocate their resources more efficiently. This leads to the use of better technologies and higher input intensity, thus increasing crop productivity and income.

2.5.4 ROBUSTNESS CHECKS

To test the robustness of the PSM estimates, we used two alternative methods to evaluate the effects of adopting digital extension services, as explained above. The ATTs obtained with the IPWRA method are shown in Table 2.6. They are very similar to those obtained with PSM in terms of both their size and significance levels. The OLS results with the inclusion of WTP to control for unobserved heterogeneity are shown in Table A.4 in Appendix A. These results are also very similar to both the PSM and IPWRA results. Hence, we conclude that our estimates are robust to variations in the estimation method.

Table 2.6: Impact of adopting digital extension services on agricultural performance (IPWRA results)

Outcome variable	**ATT**	**Robust SE**
Number of crops grown	0.793**	(0.378)
Seed expenditure per acre (log)	0.256***	(0.073)
Fertilizer expenditure per acre (log)	0.121**	(0.052)
Pesticide expenditure per acre (log)	0.182***	(0.065)
Total expenditure per acre (log)	0.164***	(0.052)
Crop productivity (log)	0.178***	(0.053)
Crop commercialization	0.060***	(0.022)
Crop income (log)	0.291***	(0.090)

ATT: average treatment effect on the treated. IPWRA: inverse-probability weighted regression adjustment.
* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level

Using PSM, we also carried out an additional robustness check related to the covariates used for the calculation of the propensity scores. Three of the variables, namely mobile phone ownership, off-farm income and peer groups, may potentially be endogenous. Using endogenous variables for propensity score calculations is unproblematic as long as these are not affected by the "treatment" (Caliendo & Kopeinig, 2008; Heckman & Vytlacil, 2005). This condition likely holds in our case, as we do not expect that mobile phone ownership or off-farm income are affected by digital extension service adoption. Nevertheless, we tested how the ATT estimates change when we exclude these potentially endogenous variables in the logit regression used to calculate the propensity scores. The ATTs are very similar to the original ones (see Table A.5 in Appendix A), thus further underlining the robustness of the estimates.

Another concern may be related to the fact that we express most of the outcome variables in logarithmic form, even though several include zero or – in the case of crop income – even negative observations (see Table A.3 in Appendix A), for which the logarithm is not defined. It should be noted that the number of households with zero or negative observations for the outcome variables is relatively small and mostly confined to the group of non-adopters. Very few of these households with zero or negative observations were selected as relevant matches based on their propensity scores. Nevertheless, we reran the PSM estimates also in linear form, without taking logs, and obtained similar results. For some of the outcome variables, the estimated ATTs even increased. With the outcome variables expressed in linear form, the digital extension effect on crop productivity increased to 21%, and the effect on crop income increased to around 40%. Hence, using the log-transformation seems to lead to conservative estimates.

2.5.5 Sensitivity to potential hidden bias

The PSM estimates of the ATTs may still be biased if any unobserved variables affect treatment assignment and that are also correlated with the outcome variables. Using the original PSM estimates, we analyse how sensitive our results are to such potential hidden bias by calculating Rosenbaum bounds (DiPrete & Gangl, 2004). Rosenbaum bounds estimate critical levels of hidden bias (Γ) for the ATTs at which the conclusion of a positive treatment effect would have to be challenged. The results are shown in Table 2.7.

Table 2.7: Critical level of hidden bias (Γ)

	Nearest neighbour matching	**Radius matching**	**Kernel matching**
Number of crops grown	1.30	1.15	1.20
Seed expenditure per acre (log)	1.15	1.45	1.40
Fertilizer expenditure per acre (log)	1.30	1.40	1.45
Pesticide expenditure per acre (log)	1.30	1.45	1.45
Total input expenditure per acre (log)	1.35	1.60	1.65
Crop productivity (log)	1.40	1.50	1.50
Crop commercialization	1.40	1.30	1.30
Crop income (log)	1.30	1.45	1.50

The robustness of the ATTs to potential hidden bias varies across the outcome variables and the three matching methods (Table 2.7). A value of 1.30 for the number of crops grown and the nearest neighbour matching algorithm means that the respective ATT would remain positive and significant at the 90% level even if there were hidden bias up to a magnitude of 30% (meaning 30% systematic difference between treatment and control group in terms of unobserved factors even after matching). Only if there were hidden bias of more than 30%, the ATT would turn insignificant. Remember that when estimating propensity scores for matching we did not only include a large number of farm and household covariates but also a WTP estimate as a proxy for relevant unobserved factors. Against this background we expect that any remaining hidden bias would be lower than 30%. For many of the other outcome variables, the critical levels for hidden bias are larger than 1.30 (Table 2.7), meaning that the conclusion of significantly positive treatment effects are fairly robust.

2.6 CONCLUSION AND POLICY IMPLICATIONS

Traditionally, the diffusion of agricultural information in developing countries has been promoted through the public extension service, wherein extension agents visit and educate individual farmers or farmer groups. This traditional way of information dissemination has two major drawbacks. First, as personal visits are associated with high transaction costs, only a very limited number of farmers can be reached. Second, the information provided through this channel is often fairly generic and not necessarily well adapted to each farmers' specific needs and conditions. Using digital approaches and technologies can potentially improve the effectiveness of agricultural extension services by reducing transaction costs and improving the quality of the information provided. Data-driven algorithms can be used to tailor information to the specific conditions of individual farmers. However, research on the actual effectiveness of such personalized digital extension approaches in the small farm sector is still very limited.

In this study, we collected and used data from smallholder vegetable farmers in eastern India to analyse the effects of personalized digital extension services on agricultural performance. The digital agri-tech platform that had recently been launched in the study region provides advice on which types of crops to grow and inputs to use, considering the weather, soil, and other agronomic as well as socio-economic conditions of each farmer. For the analysis, we looked at various outcome variables such as crop diversity, input intensity, crop productivity, levels of commercialization, and income.

As farmers decided themselves whether or not to adopt the digital extension services, the evaluation of effects needed to deal with possible issues of selection bias. We employed propensity score matching to reduce bias due to observed heterogeneity between digital extension service adopters and non-adopters. Moreover, we used a willingness to pay (WTP) variable as an additional covariate in the propensity score model to also reduce possible bias from unobserved heterogeneity. We used and compared different matching algorithms and also employed other econometric methods as additional robustness checks.

Our results show that adopting digital extension services has positive and significant effects on all outcome variables: crop productivity is increased by about 18%, crop income is even increased by 25%. Based on these findings, we conclude that digital approaches and technologies can be effective tools to improve personalized agricultural extension and promote smallholder productivity and income.

The agri-tech platform in the study region is still relatively simple and can be further improved. So far, the services provided concentrate only on the input side, although there are plans to extend the services and use the platform to also link farmers directly to retailers and consumers. Technological developments in areas such as open-source software and big data analytics may further improve the types of services provided. In the Indian example analysed here, the services are provided free of charge to farmers through a social business enterprise. However, given the magnitude of the benefits, farmers may also be willing to pay a certain amount for such digital services, as indicated by significantly positive WTP estimates in our analysis. Nevertheless, some public support may be needed to make digital extension services effective and accessible for a large number of farmers. For instance, certain infrastructure elements – such as roads, electricity, telephone network, and internet coverage – are important preconditions for digital service providers to become active in a region. Besides, a minimum level of computer and digital literacy is required either among farmers or at least among local intermediaries. Therefore, from a policy perspective, investments in rural road and ICT infrastructure, in promoting digital literacy among rural households, and in creating an enabling business environment for related entrepreneurial activities are important steps towards fostering agricultural innovation and equitable growth in the small-farm sector.

In closing, four limitations of our study shall briefly be discussed, which may also encourage follow-up research. First, our analysis of impacts relies on cross-section observational data where the establishment of causality is difficult. Although we tried to deal with issues of endogeneity to the extent possible, follow-up research with panel data and/or experimental approaches could be useful to further improve the identification strategy. Second, the results from one example of an agri-tech platform in one region of eastern India should not be generalized. Additional studies in other contexts would be useful to increase the external validity of the results. Third, we concentrated on a few outcome variables related to crop production and income, as this is what the agri-tech platform in the study region focuses on. Crop productivity and income are not comprehensive measures of household welfare. Future studies could analyse other important outcomes related to food security, time allocation, and gender roles, among others. Fourth, we looked at effectiveness in terms of improving agricultural performance without considering the costs of providing and using the digital services. Studies on the cost-effectiveness would be useful to gain further policy-relevant insights.

CHAPTER 3: EFFECTS OF ELECTRONIC MARKETPLACE ON PRICES, SPIKES IN PRICES AND PRICE DISPERSION: A CASE-STUDY OF THE TEA MARKET IN INDIA*

ABSTRACT

Asymmetric price information and costly search often restrict buyers and sellers in developing countries from accessing distant markets. Electronic marketplaces have the potential to reduce transaction costs and improve market performance. Using monthly panel data from 2000 to 2017 and applying a fixed-effects approach with Driscoll and Kraay standard errors to deal with spatial and temporal correlation, this study provides empirical evidence on the effects of electronic markets on prices, spikes in prices, and price dispersion of an agro-based commodity in India. The results suggest that the introduction of electronic markets reduced prices and spikes in tea prices by about 2% between 2000 and 2017. Further, electronic marketplaces initially increased price dispersion between markets by about 11-14%, but over time with further reduction in market friction, price dispersion reduced by 16%.

3.1 INTRODUCTION

Agriculture markets in developing countries are characterised by asymmetric price information which results in wide variation in prices temporally and spatially (Abdulai, 2000; Jensen, 2007; Moser et al., 2009). Information problems often result in the inability to undertake mutually beneficial exchange because search costs are so high that buyers and sellers are either unable to find each other or are not able to acquire enough information to confidently proceed with a transaction (World Bank Group, 2016). Further, high entry costs to local markets enable oligopsonists to keep selling prices below competitive levels (Meenakshi & Banerji, 2005; Rogers & Sexton, 1994; Sexton, 1990; Shimamoto et al., 2015), while on the buyers' end, market power by intermediaries keep prices above marginal cost (Burdett & Judd, 1983; Salop & Stiglitz, 1977; Stahl, 1989, 1996; Varian, 1980). Thus, high information costs reduce the

* This essay is co-authored by Lukas Kornher. I conceptualized the research, curated the data, developed the methodology, carried out the formal analysis, and wrote the manuscript. Lukas Kornher commented at various stages, and edited the manuscript.

extent of market exchange and lead to economy-wide Pareto inefficiencies (Greenwald & Stiglitz, 1986; Stiglitz, 1988). Under these situations, an important policy question in the context of developing countries is: how can agricultural markets be made more efficient? Earlier literature has highlighted that information technology can reduce information asymmetries and make markets more efficient (Aker, 2010; Jensen, 2007). Jensen's (2007) paper showed that the introduction of mobile phones improved communication capabilities, and access to market information which resulted in reduced price-dispersion across fish markets in Kerela, India. On the buyers' side, improved access to information decreased prices and increased consumer surplus, while on the sellers’ side, a fall in prices resulted in increased growth in sales volume and reduced wastage. Aker (2010) in a similar study, analysed the implications of rolling out mobile phones in grain markets in Niger and found that mobile services reduced price dispersion between markets and increased trader’s profits. Other studies that have analysed the implication of improved access to information for producers through mobile phones and market information systems (MIS) on farm gate prices have found mixed empirical evidence (Aker & Fafchamps, 2014; Fafchamps & Minten, 2012; Goyal, 2010; Haile et al., 2019; Mitchell, 2017; Shimamoto et al., 2015; Svensson & Yanagizawa, 2009).

Over the past few years with the rise of high-speed internet connections, the use of ICTs has further evolved in developing countries. Several internet-based applications and technologies are being developed which could reduce the time and monetary cost of processing and communicating information across agro-based value chains. The rapid adoption of the internet has enabled the emergence of electronic marketplaces that aggregate supply and demand by connecting buyers directly to sellers through a digital platform and it promises to reduce search costs for market participants (Baumüller, 2018; Rao et al., 2017). In developing countries, search costs make up a significant proportion of transaction costs, particularly if the traded volume is low. Several economists have asserted that electronic markets have the potential to benefit both buyers and sellers of homogenous and differentiated commodities by reducing search costs (Bakos, 1997). From a buyer’s perspective, reducing search costs to acquire information about sellers’ price and product offerings enables buyers to procure products at lower prices as a result of increased competition among sellers (Bakos, 1997; Lee et al., 1999; Smith et al., 2000). Sellers, on the other hand, can benefit by increasing sales by accessing new markets, decreasing costs to communicate information about prices and product characteristics, increasing reservation prices due to competitive bidding by new buyers or product differentiation based on quality, and reduce buyer collusion due to anonymous bidding (Bakos, 1997; Klemperer, 2004; Roy et al., 2017; Smith et al., 2000).

Previous studies that have analysed the effects of online commerce on consumer durable goods such as used cars, books, compact discs, and term life insurance in high-income countries have found mixed evidence on the impact of electronic marketplaces on prices and market efficiency. Few studies have claimed that prices have fallen and markets have become more efficient, while others have claimed that prices are higher and that the electronic marketplaces may not be as efficient as expected (Brown & Goolsbee, 2002; Brynjolfsson & Smith, 2000; Clay et al., 2001; Lee et al., 1999). Since empirical findings are varied on the implications of electronic commerce, it is important to study the consequences of electronic marketplaces on other internet markets, especially in the context of emerging economies and commodities with limited shelf-life. To the best of our knowledge, there is only one published study that analyses the impact of electronic marketplaces on market prices and farmers' profitability (Levi et al., 2020), we add to this scarce literature by analysing empirically the implications of electronic marketplaces on market performance by doing a case study of the tea sector in India. In this study, we exploit the exogenous variation of the introduction of electronic markets between 2009 and 2010 to identify its impact on prices, spikes in prices, and price dispersion.

Keeping this background in mind this study aims to answer the following research questions: 1. does the introduction of electronic marketplaces affect prices of tea and spikes in tea prices? and 2. is there an effect on market efficiency when electronic markets are introduced? Our contribution to literature is threefold. First, using a high-frequency monthly panel dataset from 2000 to 2017, we analyse the effects of the introduction of electronic marketplaces on auction prices, and price dispersion between markets in the context of a developing country. We also study the effect of electronic marketplaces on spikes in tea prices, as sudden large spikes in prices cause uncertainties to investment by buyers, sellers, and tea producers. Second, we study the implications on an agro-based commodity with limited shelf life and third we analyse the changes in market efficiency due to the introduction of electronic marketplaces over time.

The paper proceeds as follows: In section 3.2, we discuss the tea market in India and the mechanism of the introduction of electronic marketplaces. Section 3.3 discusses the conceptual framework and section 3.4 discusses the materials and methods used in the paper. Section 3.6 presents the descriptive and the econometrics results while section 3.7 concludes.

3.2 TEA MARKET IN INDIA

3.2.1 OVERVIEW OF TEA MARKET

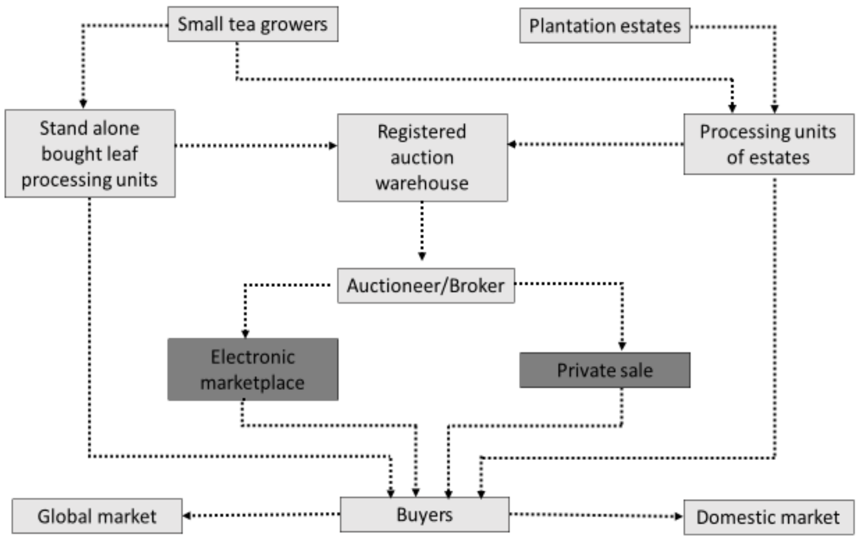
In India, tea production and processing play an important role in terms of employment, rural food security, and foreign exchange earnings. The sector employs about 1 million people, of which, about 60% are women. Further, Assam, the largest tea growing region in India (53% of total production), is one of the poorest in the country, with around 40% of the rural population living below the poverty line and about 50% of daily wage labour dependent on employment through the tea sector. In terms of foreign exchange earnings, India is the second-largest producer of tea after China, supplying around 23% of global tea production which contributes about 14% of total exports, making it the fourth-largest exporter of tea after Kenya, China, and Sri Lanka. Although tea is an important export commodity generating 0.2% of India's total export earnings, India is also one of the largest consumers of tea. Around 80% of the tea produced is consumed locally.

The tea value chain has several market participants from producing green tea leaves, processing bulk tea to selling the processed tea to commercial buyers (Figure 3.1). In the upstream segment, producers of green tea leaves are either small tea growers (less than 10 hectares of land) or large organised plantation estates[4]. The mid-stream segment includes processors who manufacture bulk tea from green leaves. This could be stand-alone processing units or factories belonging to plantation estates. In the downstream segment, once the tea is processed it is sold via 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 sell branded tea to consumers. In the tea value chain, the auctioneer is a third-party intermediary that finds buyers and sells the product on behalf of processors either through private sales or through public auctions by levying a service charge of 1% of the total value of the transaction. The auctioneer also provides services to buyers such as cataloguing tea, inspecting the quality of tea by tea tasting, providing valuation, and sending samples to buyers

[4] As per the Tea Board of India, around 44% of total tea produced in India is by small tea growers.

located in different parts of the country. For their services, to buyers, they charge a fee of 0.18% of the value of the transaction[5].

Figure 3.1: Tea value chain in India



Source: created by author

3.2.2 MARKETING OF TEA

Tea can primarily be sold through two marketing channels: private sale of processed bulk tea at negotiated prices and sale of tea competitively through public auctions in designated market areas. Public tea auctions have been the main method of marketing and distributing tea in India since 1861. Currently, on average around 47% of total tea produced in India is sold via auctions through six auction centers that sell only tea and is open to any tea manufacturer registered with the Tea Board of India. The bulk of the remaining tea is sold through direct sales at negotiated prices and a very small volume of tea is sold through three smaller auction centers. Of which two of them are accessible only to a group of producers who grow a specific type of tea and are members of a particular society.

Weekly auctions begin with bulk tea being transported from processing units to registered warehouses for sale through the appointed auctioneer. The warehouse

[5] These rates are fixed by the Tea Board of India. In comparison to the Indian rates, auctioneers in the Mombassa auction centre charge 1% from the producers and 0.5% from the buyers.

keeper creates an arrival and weight report showing the date of arrival and details regarding any damage or shortfall in arrivals. The auctioneer then catalogues, samples and values the tea before sending samples to the buyers located in different regions. These samples are disseminated 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 in designated centers to bid for tea competitively till a fair price is discovered. Public auctions are usually preferred to private sales since auctions facilitate the transaction of large quantities of tea in the shortest time, and it enables buyers to purchase broader varieties of tea and sellers to access a wider range of domestic and external markets. Auction prices also serve as a benchmark for private sales and prices paid for green leaves purchased from small tea growers.

3.2.3 INTRODUCTION OF ELECTRONIC MARKETPLACES

Between 1861 and 2009 weekly physical auctions were conducted through open outcry ascending price or English auction. The advantage of the public outcry system was that it allowed for human interactions such that buyers and auctioneers could negotiate prices based on quality. However, there existed important market inefficiencies in the physical auction system. First, big buyers often acted collusively and engaged in bid-rigging to obtain lower prices of bulk tea and transferred profits within the value chain to the retail end of the chain. Second, transaction costs for buyers to access multiple markets were high as those who wanted to participate in different auction centers across India had to have their representatives physically present in specific markets on auction dates. This increased the cost of doing business and therefore limited the number of buyers in tea markets. Third, due to existing entry barriers to new markets, search costs were substantially high and it limited mutually beneficial trade between buyers and sellers. Thus, in an attempt to make auctions more efficient such that the sum of seller revenue and buyer profits is maximized, physical auctions were replaced by electronic marketplaces between 2009 and 2010 in the tea auction centers. Transiting to electronic format aimed to increase buyer participation by reducing transaction costs, increase access to new markets and increase sale volumes. Further, making bids anonymous electronically was intended to reduce the probability of buyer collusion.

The electronic marketplace introduced in the tea sector functions using an application that is compatible with computers. It was first introduced in tea-growing regions of southern India followed by tea regions in eastern India. In May 2009, Coonoor and Coimbatore auction centers introduced electronic marketplaces followed by Kochin in July 2009. Electronic markets were first launched in Southern India because a pilot electronic marketplace was already in use by a group of few cooperative factories in Tamil Nadu in 2003 for a specific type of tea (Nilgiri tea). In the eastern region, the center at Guwahati introduced an electronic marketplace in January 2010, then Kolkata in April 2010, and finally Siliguri in October 2010. By October 2011, all auction centers had electronic marketplaces. The rules of the transaction were identical to the physical auction, except transactions were carried out 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, this enables us to study the impact of the introduction of the electronic marketplace on the market performance of tea.

Initially, when electronic marketplaces were introduced it still required buyers to register separately for each center to participate in multiple markets i.e., a buyer registered in the Guwahati auction center could transact in another auction center only with a separate registration. In June 2016, the rules of inter-market electronic trading were altered by allowing market actors registered in any of the six centers to transact anywhere with a single registration. This modification of the rules of trading is commonly called the 'Pan-India electronic auction' in the tea industry and it was done to further reduce transaction costs for buyers and improve price discovery via the digitised platform. This is the reform that may have mattered more and we therefore, use this structural break to study the effects of the electronic marketplace on price dispersion between auction centers when market friction is further reduced over time. In the new system of Pan India electronic auction, sellers of tea remained localized and could only offer tea lots in the auction center that they were registered in, while buyers could bid in any center without being locally registered. In Figure: B.1 in Appendix B, we show the number of buyers and sellers before and after the introduction of the electronic marketplace of the largest tea auction center in India— Guwahati tea auction center— which contributes around 31.5% of total market arrivals. This clearly shows that after Pan-India electronic auction was introduced, the number of buyers and sellers increased in this auction center.

3.3 CONCEPTUAL FRAMEWORK

In agricultural commodity markets, electronic marketplaces are expected to provide information about the existence of a seller and a buyer and in ensuring competitive price discovery. Theoretically, electronic marketplaces connecting buyers to sellers directly through a digital interface are expected to reduce search costs (Bakos, 1997). Reduction in search costs can facilitate the amount of search buyers conduct, which will in turn increase price competition among sellers. This is expected to make markets more efficient by reducing price dispersion. In an efficient market where information about product prices is well disseminated, sellers' prices are expected to convergence to a single price such that any seller that charges prices significantly above marginal cost will lose buyers (Lee et al., 2003). Thus, from a buyer's perspective, reducing search costs to acquire information about sellers' price and product offerings through a digital interface enables buyers to procure products at lower prices and also enables them to make more informed bids.

While it is expected that electronic marketplaces increase competition amongst sellers but market prices may not always decrease. It may also increase if sellers can product differentiate and offer higher quality products through online trade (Lee et al., 1999), or if online trade reduces buyer collusion through anonymous bidding, or increases demand for products due to entry of new buyers. Further, price dispersion across markets may also increase due to the immaturity of internet markets (Lee et al., 2003) or existence of market agents with heterogeneous search costs (Brown & Goolsbee, 2002) or due to the ability of sellers to product differentiate based on quality and trust (Brynjolfsson & Smith, 2000). The seller thus can benefit by increasing sales by accessing new market, improving their bargaining power, decreasing costs to communicate information about prices and product characteristics, and improving transparency in the process of price discovery by reducing buyer collusion (Bakos, 1997; Klemperer, 2004; Roy et al., 2017; Smith et al., 2000).

Further, electronic marketplaces may not bring down search costs to zero on introduction (Brown & Goolsbee, 2002). It is likely that differences in buyers' and sellers' ability to adopt a new technology initially increase the search cost for market actors, especially in the context of developing countries where digital literacy is low. From the seller's perspective, the initial introduction of a new technology could cause uncertainties in price setting and adjustments at the margin of prices over quality. Further from the buyers' point of view, earlier literature on the effects of search costs on equilibrium price distribution suggest that buyers are heterogeneous in terms of their search costs, such that a small proportion of buyers have no search cost and the remaining have a positive search cost (Stahl, 1989). According to this strand of literature, buyers with positive search costs stop searching whenever they find a price below their reservation price, while buyers with zero search costs get price quotes from all sellers and buy from the lowest-priced one (Brown & Goolsbee, 2002; Stahl, 1989). Thus, as the proportion of uninformed buyers increases, market prices converge to the monopoly price and when the proportion of fully informed buyers increases, competition rises amongst the sellers, and prices converge to the competitive price. In other words, as the search cost decreases to zero, market prices converge to the degenerate distribution at marginal cost (the Bertrand result) (Stahl, 1989).

In the case study we analyse, during physical auctions, each lot of tea was sold sequentially, however, when transactions were made electronically multiple lots were sold simultaneously in a given period. Since many concurrent auctions for similar grades of tea were being conducted electronically, it is expected that for a fraction of buyers who did not have experience with electronic transactions or had low digital literacy, search costs must have increased in the form of time, effort, and analytical ability required to identify the set of potential auctions. Consequently, buyers with high search costs possibly conducted narrow searches and identified only a subset of the available auctions. While those experienced buyers with low search costs were able to conduct broad searches and identify all available auctions. Thus, initially, price dispersion between markets probably increased because unaware buyers bid up the prices of some auctions over others (Backus et al., 2014). However, over time as markets matured with more experience with the use of digital technology and also with the introduction of the Pan-India electronic auction which further reduced search costs for buyers, it is expected that the proportion of unaware buyers reduced. Thus, we expect the following results through our empirical analysis: 1. when there are asymmetric search costs amongst buyers and sellers, price dispersion will exist in equilibrium, 2. as the share of buyers with no search costs increases we expect prices to fall due to increased competition amongst sellers and 3. in the context of developing countries, where digital literacy is low, initial differences in buyers' and sellers' ability to adopt new digital technologies are likely to increase search costs, and as markets mature and market agents gain experience, search costs are likely to reduce. Thus, we expect price dispersion to rise at first and then to fall over time. Moreover, electronic marketplaces such as the one introduced in the tea sector in India also provide information about the last sold prices of different grades of tea by different sellers and base prices for each lot. Thus better access to information also enables buyers to make more informed bids by reducing forecasting errors. This would result in a reduction in spikes in market prices of tea.

3.4 MATERIALS AND METHODS

3.4.1 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 for the period 2000 to 2017. Indian tea auction prices and market arrivals data was compiled from the annual tea statistics market report released by J Thomas and Co. Pvt Ltd. India has in total 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 centers that are actively functional. Thus, the sample of tea auction centers for this study is six: Guwahati, Kolkata, Siliguri, Kochi, Coonoor, and Coimbatore. Data for Jalpaiguri, auction center was not available because on most auction days there were no sales[6]. Furthermore, Teaserve is an auction center that markets tea for a group of cooperative tea factories, while the Amritsar auction center, markets a small volume of tea produced by Kangra Tea Planters Society. Data from the latter two are not included in the study because these two auction 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 auction prices in international markets were compiled from World Bank commodity price data. Diesel prices were collected from Petroleum Planning and Analysis Cell and Indian Oil Corporation Limited.

[6] The Jalpaiguri auction center is located in West Bengal where the Calcutta auction center is also located. The Calcutta auction center which started functioning in the 1970s is a much older auction center than the Jalpaiguri center (started in 2005) and most of the tea produced in the state of West Bengal is sold through the Calcutta auction center.

3.4.2 EMPIRICAL STRATEGY

1. Effects of electronic marketplaces on price levels and spikes in tea prices

To estimate the effects of electronic marketplaces on prices of tea, the following panel data fixed effects regression model is used:

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

where t is the month for the period 2000 and 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 1 in month t if an auction center introduced an electronic marketplace. $X_{i,t}$ is a vector of time-variant contextual variables that affect prices of tea such as auction arrivals, world tea prices, domestic diesel prices, and rainfall. S_t is a vector of month dummies to control for seasonality of tea production; α_i is the auction center fixed effect to control for all unobserved time in-variant difference between markets such as geographical location, quality difference based on region and market size, and T_t is the time trend. In certain specifications, auction-center-specific time trends are also included. We also expect that 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 mean. Further, to estimate the impact of electronic marketplaces on spikes in tea prices we estimate the following equation:

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

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 period-over-period prices of tea. $V_{i,t}$ is a vector of time-variant contextual variables that affect spikes in prices of tea such as spikes in production (or supply shocks), a spike in diesel prices, average rainfall in tea growing regions, world prices of tea. Similar to the previous specification, S_t is a vector of month dummies to control for seasonality of tea production; γ_i is the auction center fixed effect, T_t is the time trend and $\eta_{i,t}$ is a random error term.

Since in this study, 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. Equation (1) and equation (2) are estimated by OLS regression of the outcome variables on the contextual variables as specified and N individual dummy variables representing the number of auction centers, which yields the within estimator for β along with estimates of the N fixed effects (Cameron & Trivedi, 2005). The LSDV estimator of β is unbiased and consistent when either N or T is large (Hsiao, 2014).

The validity of the results depends on whether the variables used in the model are stationary. It is well accepted that time series variables often show spurious association 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, we use a Fisher-type method developed by Choi (2001) to test for stationarity, where the null hypothesis is that all the panels contain a unit root. We present the results of the stationarity tests using augmented Dickey-Fuller and Phillip Perron panel data unit-root tests in Table B.1 in Appendix B. Both the tests suggest that we reject the null hypothesis of a unit-root at a 1% level of significance for all the transformed variables used in our analysis. Thus we treat all the time-series variables as stationary.

Further, cross-sectional time-series data usually have issues of heteroscedasticity, contemporaneous or spatial correlation, and auto-correlation. In this study, auction centers located in different regions are likely to be subjected to observable and unobservable common disturbances which could cause the residuals from one cross-section to be correlated with those of another and also over time. If the unobservable common factors are not correlated with the control variables, then the coefficient estimates using the standard fixed effects estimator is 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, and 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 by the fixed effects (within) regression. The standard errors are robust to spatial and temporal dependence when the time dimension becomes large. Further, this nonparametric technique of estimating standard errors does not restrict the number of panels and is an appropriate method of estimation in case of a small panel and large time dimensions (Driscoll & Kraay, 1998; Hoechle, 2007). Thus, the fixed effects estimator is implemented in two steps. In the first step, all variables are within transformed, and the second step estimates the transformed regression model by pooled OLS estimation with Driscoll and Kraay standard errors (Hoechle, 2007).

Additionally, it is expected that market performance at time t depends on performance in the previous period. Therefore, the lagged variable of the dependent variable is also included as a control variable in different specifications of equation (1). As is well known, the LSDV estimator with a lagged dependent variable as a regressor is biased and inconsistent when the time dimension of the panel (T) is small. Nickell (1981) and Kiviet (1995, 1999) derive an approximation for the inconsistency of the LSDV as N approaches infinity, which is bounded by order $T^{-1}, N^{-1}T^{-1}$ and $N^{-1}T^{-2}$. Thus, the LSDV estimator is asymptotically valid only when the time dimension of the panel is large (Baltagi, 2005; Hsiao, 2014; Kiviet, 1995). Since in this study the time dimension is large (T=216) relative to the number of cross-sectional units (N=6), the bias is likely negligible. Further, the bias is expected to be more severe for the coefficient of the lagged dependent variable (Judson & Owen, 1999) than for the coefficient of the dummy variable that represents the introduction of the electronic marketplace which is of primary interest in this study.

2. Effects of the electronic marketplace on market efficiency

Market efficiency is measured in terms of spatial price dispersion between markets by comparing price dispersion between pairs of auction centers (markets) where both centers have access to electronic-marketplace at a particular point in time, to the price difference between pairs of centers where at least one center lacks access to electronic-marketplace. This approach is similar to the empirical method used by Aker (2010) and Andersson et al. (2017). It is expected that when markets become more efficient then the absolute price dispersion between markets should reduce. Thus, to address the second research question on the effects of electronic marketplaces on market efficiency the following model is estimated.

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

where, $\left|p_{jt} - p_{kt}\right|$ is the log of absolute price dispersion of prices in auction centre j and k at time t. $E_{jk,t}$ is a dummy variable equal to 1 if both auction centres j and k have an electronic marketplace in time t, otherwise 0. $Z_{jk,t}$ *is a vector of* time-variant contextual variables that affect price dispersion between two auction centre such as absolute arrivals dispersion, average rainfall in the tea-growing region where the markets are located, world prices of tea, and spike in diesel prices. Similar to the specification in equation (1) and equation (2), S_t is a vector of month dummies to control for seasonality, T_t is time trend, θ_{jk} are market-pair fixed effects to control for all unobserved time in-variant difference between market-pairs and $\varepsilon_{jk,t}$ is a random error term. Further, 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 alternate specification of equation (3). Equation 3 is estimated using an LSDV estimator and in another specification, Driscoll and Kraay standard errors for the coefficients are estimated to deal with spatial and temporal dependence.

We also analyse the effects of the introduction of the Pan-India electronic auction on price dispersion by estimating equation (4) with Driscoll and Kraay standard errors. Here, the specification is the same as equation (3) except for an additional dummy variable $I_{jk,t}$ is included 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 via the digitised platform. Thus, to understand the effects of Pan-India electronic auctions we are interested in the coefficient γ_2.

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

3.5 MEASUREMENT OF VARIABLES

- **Price level and spike in tea prices:** Monthly average tea prices in each auction centre is taken from the tea statistics market report compiled by J Thomas and Co. Pvt Ltd. Average prices in these reports are calculated by taking the unweighted average weekly auction prices of different grades of tea (loose leaf tea and dust tea). For the analysis, we use real tea prices by deflating the raw data by the wholesale price index at 2012 prices. We measure a price spike as a temporary rise or fall in prices due to short term shocks (Tadesse et al., 2014). Spike in auction prices is measured as log($P_{i,t}$)-log($P_{i,t-1}$), where $P_{i,t}$ is the real price of tea at time *t* in auction centre *i*.

- **Price dispersion:** Price dispersion is calculated by creating a panel dataset of pairs of auction centers and taking the absolute difference in real prices between auction center *j* and *k* at time *t*.

- **Market arrivals and arrivals dispersion:** Month-wise market arrivals in each auction centre is also taken from the tea statistics market report compiled by J Thomas and Co. Pvt Ltd. The report averages weekly arrivals of different grades of tea to get the average monthly arrivals in each center. Using the market-pair dataset, arrivals dispersion is calculated by taking the absolute difference in arrivals between auction center j and k at time t.

- **World tea price index***:* Besides India, Kenya and Sri Lanka are big tea producing countries in the world, therefore, a monthly world tea price index is created by taking average auction prices in Mombasa and Colombo auction centres and deflating prices by 2012 prices.

- **Spike in diesel price:** Monthly diesel prices are calculated by averaging daily retail prices in the closest metropolitan city to where the auction center is located. Spike in diesel prices is measured as log($D_{i,t}$)-log($D_{i,t-1}$), where $D_{i,t}$ is the real price of diesel (Rs/litre) at time t in the closest metropolitan city to where the auction center i is located.

- **Rainfall:** In tea-growing regions, sellers are localised and can only offer tea lots in the center they are registered in. Due to high transportation costs, this is usually the auction center in a specific state. Thus, in equation (1), the average rainfall in tea growing regions is calculated by taking the average measurement of rain gauges installed in tea growing areas of different states where each auction center is located**.** For example, since the Guwahati auction center is located in Assam; average rainfall is calculated by taking the mean of three rain gauge readings located in North Bank, Upper Assam, Tocklai. Similarly, for auction centers located in West Bengal, average monthly rainfall is measured by taking the mean of four rain gauges located in Cachar, Terrai, Darjeeling, and Nagrakata. The same is done for the auction centers located in South India. For equations (2) and (3), the average rainfall is calculated as the mean of rainfall in tea growing regions of the states where auction centres j and k are located.

- **Production and spike in production:** Monthly production of tea is calculated by summing district-wise production in each state where the auction center is located. Spike in tea production (or supply shock) is measured as log($Z_{i,t}$)-

$\log(Z_{i,t-1})$, where $Z_{i,t}$ represents the total tea produced in the region where the auction center i is located.

3.6 RESULTS AND DISCUSSION

3.6.1 DESCRIPTIVE ANALYSIS

Panel A in Table 3.1 presents the summary statistics of the market level data. The data show that there is a statistically significant difference in average auction prices before and after the introduction of electronic marketplaces, however, there is no significant difference in spike in prices of tea. Without controlling for any other factors, Table 3.1 highlights that average prices of tea in real terms marginally increased from 100.24 Rs/kg to about 103.86 Rs/kg after the introduction of electronic marketplaces. Likewise, there are significant differences in market arrivals, prices of diesel and world tea prices in the pre-intervention period as compared to the post-intervention period. However, the difference in average rainfall in the tea-growing regions between the two periods is statistically not significant. Further, in Panel B the summary statistics for the market-pair data are presented. The data indicate that without controlling for other covariates the unconditional average price dispersion between markets significantly increased by 3.78 Rs/kg after the introduction of the electronic marketplace as compared to the period 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 average prices of tea and price dispersion between markets are unconditional means without considering other factors that might affect market performance.

Figure 3.2 presents monthly prices of tea in real terms in each auction center between the years 2000 and 2017 and Figure B.2 in Appendix B plots spikes in tea prices. The vertical dotted lines in the graphs represent the month in which an electronic marketplace was introduced in each auction center. The graphs in Figure 3.2 suggest that there are considerable spikes in tea prices in all markets in India. This is also visually observable in the graphs plotting month-on-month spike in tea prices in Figure B.2 in Appendix B. Further, we plot the absolute price difference between market pairs in Figure B.3 in Appendix B; this too shows substantial volatility before and after the introduction of an electronic marketplace. To understand the impact of the introduction of the electronic marketplace on tea prices, spikes in prices, and price dispersion we estimate our econometric models in the next section.

Table 3.1: Summary statistics

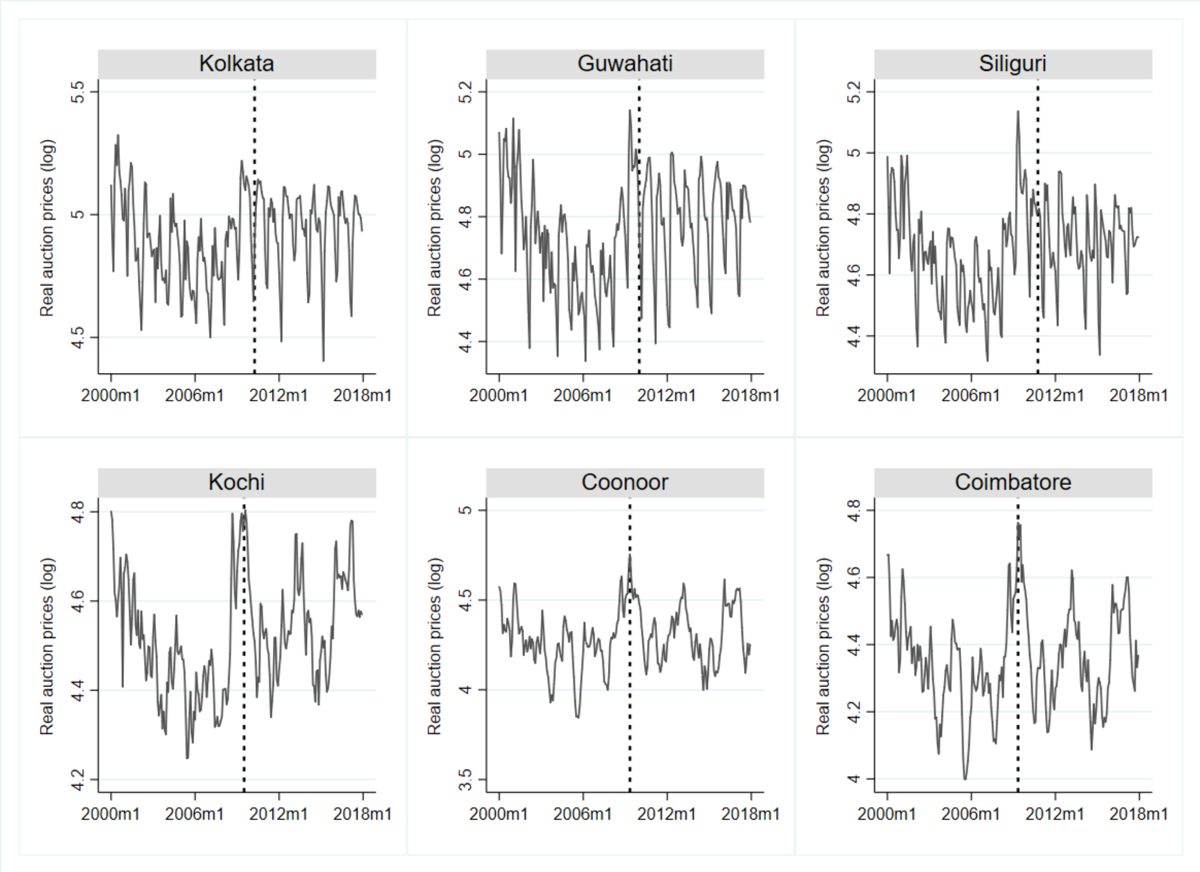
	Before the introduction of electronic marketplace				After the introduction of electronic marketplace			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Panel A: Market level data								
Nominal auction prices (Rs/kg)	62.73	21.01	28.98	142.43	108.99***	31.54	51.30	195.57
Real auction prices (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 (in tonnes)	6,866.37	4,828.25	393.00	23,553	7,652.14***	6,103.34	468.00	2,7834
Nominal diesel prices (Rs/litre)	26.85	7.34	15.10	40.52	50.32***	8.36	15.10	63.24
Real diesel prices (Rs/litre)	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 (in mm)	218.99	220.57	0.00	1,356.68	227.15	231.44	0.00	1,249.43
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			
Panel B: Market-pair level data								
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 (in tonnes)	5,265.85	4,363.89	11.00	21,669.90	6,755.33***	5,587.44	0.57	26,237.94
Average rainfall in tea growing region of market j and k (in mm)	221.06	207.23	0.00	1,111.67	223.39	209.89	0.00	1,079.18
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
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			

Mean difference before and after the introduction of electronic marketplaces * significant at 10% level, ** significant at 5% level, ***significant at 1% level.

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

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

Figure 3.2: Prices of tea in different markets in India



Auction prices have been deflated by the wholesale price index at 2012 prices. Tea prices are presented in logarithmic form. Vertical dotted lines depict the month in which an electronic marketplace was introduced in each auction centre. Coonoor and Coimbatore introduced the electronic marketplace in May 2009, Cochin in July 2009, Guwahati in January 2010, Kolkata in April 2010, and Siliguri in October 2010.

3.6.2 EFFECTS OF ELECTRONIC MARKETPLACE ON PRICES AND SPIKES IN PRICES

In this section, we analyse the effects of electronic marketplace on the prices of tea and spikes in tea prices. In Table 3.2 we present seven different fixed effects specifications of equation (1) with price levels as our outcome variable. Without controlling for any other factors that affect the prices of tea, column (1) shows that electronic marketplaces have a positive and significant effect on prices. However, once we control for other factors, the sign of the coefficient of electronic marketplaces is reversed (column 2-7). In column (2) contextual variables such as tea arrivals in auction markets, world prices of tea, spike in diesel prices, and average rainfall in tea growing regions are included along with other variables to control for seasonality, common time trend, market-specific time trends, and market fixed effects. Column (2) shows that electronic marketplaces reduced auction prices of tea by 4.4%. In column (3), we add the lagged dependent variable to allow for market performance at time *t* to depend on performance in the previous period. Adding lagged prices as a covariate into 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) allows to distinguish between the short and long-run adjustments. However, due to a possible inconsistency of the LSDV estimator concerning the lagged dependent variable, we abstain from interpreting the long-run adjustment.

Further to adjust the estimates for temporal and spatial dependence, the standard errors are clustered by quarters in column (4) and it is clustered by markets in column (5), respectively. In column (6) and column (7), the main model is presented with Driscoll and Kraay standard errors, which deal with heteroscedasticity, autocorrelation, and contemporary correlation. The results are still negative and statistically significant. Thus, suggesting that the estimates are robust to different specifications with and without lagged dependent variables and also after dealing with temporal and spatial dependence. Using the most conservative estimate, Table 3.2 suggests that the introduction of electronic marketplace reduced auction prices of tea by about 2.1% as compared to the period when physical open outcry auction transactions were prevalent. These results are aligned to the consumer search theory which predicts that as search cost reduces, competition amongst sellers increases and overall prices of commodities fall in equilibrium, thus, increasing the welfare of buyers. The overall effect on producer surplus depends on the effect of electronic marketplaces on overall sale volumes. Since we do not have monthly data on auction sales, we are unable to comment on the overall benefits of electronic marketplaces on sellers.

Additionally, as one would expect, the control variables used in the analysis suggest that there is a significant and negative relationship between domestic auction prices and arrivals of tea in each auction center and a positive association between auction prices and world tea prices. Admittedly, 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 B.2 in Appendix B. The stability of the coefficient estimate of the electronic auction dummy makes us confident that its estimation is consistent. The coefficient of the variable rainfall shows a negative association with auction prices. This is because tea withering which is an important part of the processed tea manufacturing procedure is dependent on the level of atmospheric humidity. When humidity increases, the withering process is altered and subsequently, the quality of tea and its price is affected. Additionally, the coefficient of the lagged auction prices suggests that prices of tea in period *t-1* have a significant and positive effect on prices of tea in period *t*.

Table 3.2: Effects of electronic marketplace on price levels

	Dependent variable [$\boldsymbol{log(P_{i,t})}$]						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Electronic auction (dummy)	0.038**	-0.044***	-0.026***	-0.026*	-0.026*	-0.026**	-0.021*
	(0.015)	(0.016)	(0.009)	(0.013)	(0.010)	(0.013)	(0.012)
Auction arrivals (log)		0.023**	-0.070***	-0.070***	-0.070***	-0.070***	-0.052***
		(0.012)	(0.008)	(0.011)	(0.013)	(0.009)	(0.008)
World tea price index (log)		0.209***	0.079***	0.079***	0.079***	0.079***	0.069***
		(0.027)	(0.016)	(0.022)	(0.008)	(0.023)	(0.022)
Rainfall (log)		-0.005	-0.005**	-0.005*	-0.005**	-0.005*	-0.003
		(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Lagged rainfall (t-1) (log)		0.006	0.002	0.002	0.002	0.002	-0.005
		(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Spike in diesel price		0.304**	0.180*	0.180	0.180**	0.180	0.175
		(0.140)	(0.101)	(0.173)	(0.049)	(0.175)	(0.172)
Lagged auction prices (t-1) (log)			0.841***	0.841***	0.841***	0.841***	0.851***
			(0.018)	(0.025)	(0.027)	(0.020)	(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 x monthly time dummy	No	No	No	No	No	No	Yes
Observations	1,296	1,262	1,262	1,262	1,262	1,262	1,262
R-squared††	0.005	0.722	0.911	0.911	0.911	0.728	0.837

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

$P_{i,t}$ is the auction prices of tea in period t in auction center *i*. Robust standard errors in parentheses (column 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 wholesale price index at 2012 prices. † World tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices. †† Column (6) and column (7) presents within R-squared

In Table 3.3 we present several fixed-effect specifications of equation (2) with spike in the price of tea as the outcome variable. Without controlling for other factors, column (1) shows that electronic marketplace does not have a significant effect on our outcome variable, however, once we include other control variables such as a spike in production of tea (or supply shocks), world prices of tea, spike in diesel prices and 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 seasonality, we find that electronic marketplaces have a significant and negative effect on spikes in tea prices (column 2-6). Similar to the previous table, 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) and column (6), we present the main results with Driscoll and Kraay standard errors. The results suggest that electronic marketplace reduced spikes in tea prices by about 2.4% as compared to the period when tea auctions were conducted physically. Reduction in spikes in tea prices has important implications for investors in the tea market. The decrease in sudden price changes reduces uncertainties for buyers, sellers, and tea producers and enables them to make informed decisions about investments. Further, the coefficients of the control variables suggest that spike in the production of tea (or supply shocks) and an increase in world tea prices have a positive and significant effect on spikes in tea prices in domestic markets.

Table 3.3: Effects of electronic marketplace 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	-0.024**	-0.024*	-0.024***	-0.024**	-0.024**
	(0.006)	(0.009)	(0.012)	(0.006)	(0.011)	(0.011)
Spike in production of tea (%)		0.013***	0.013***	0.013*	0.013***	-0.003
		(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
World tea price index (log)		0.049***	0.049**	0.049***	0.049**	0.049**
		(0.016)	(0.022)	(0.009)	(0.022)	(0.021)
Rainfall (log)		0.003	0.003	0.003	0.003	-0.000
		(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Spike in diesel price (%)		0.142	0.142	0.142**	0.142	0.165
		(0.112)	(0.177)	(0.042)	(0.179)	(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 x monthly time dummy	No	No	No	No	No	Yes
Observations	1,290	1,276	1,276	1,276	1,276	1,276
R-squared††	0.000	0.225	0.225	0.225	0.377	0.561

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.
$P_{i,t}$ is the auction prices of tea in period t in auction center *i*. Robust standard errors in parentheses (column 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 wholesale price index at 2012 prices.
† World tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices.
†† Column (6) presents within R-squared

3.6.3 EFFECTS OF ELECTRONIC MARKETPLACE ON PRICE DISPERSION

Table 3.4 presents different fixed effect specifications of equations (3) and (4), where we analyse the effects of electronic marketplace between pairs of auction centers on log of absolute price dispersion and changes in efficiency over time. We interpret the results in column (1) to column (7) as initial effects of the introduction of electronic marketplaces on market efficiency, while in column (8) the coefficient of the dummy variable 'Pan

India electronic transaction' is interpreted as changes in market efficiency over time due to further reduction in search cost. For the estimations in column (1) to column (7), we restrict the data up to May 2016, while in column (8) we use the full sample from January 2000 to December 2017. It can be observed that initially when electronic marketplaces were introduced, price dispersion between markets increased (columns 1 to 7). Without controlling for any factors that affect price dispersion between markets, column (1) shows that price dispersion between markets increased by 13%. In column (2) control variables that affect price dispersion between markets such as world tea prices, dispersion in arrivals between markets, average rainfall in tea growing regions, 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 trend, and a quadratic time trend to control for non-linear trend. In column (3) group-specific time trends are also included. Column (2) and column (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 introduction of the electronic marketplace increased price dispersion by 14%.

Further to deal with temporal and spatial dependence, the standard errors are clustered by quarters in column (5) and it is clustered by markets in column (6). In column (7), Driscoll and Kraay 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. Post-June 2016, when electronic trading was made flexible to further reduce search costs, price dispersion between markets reduced. In Table B.3 in Appendix B, we present two more specifications with an interaction between dummy variables representing 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 and in Table B.4 in Appendix B we present the results of equation (2) and equation (3) without absolute auction arrivals between markets as a control variable. These results are very similar to the results presented in column (7) and column (8) in Table 3.4. This suggests that initially when electronic marketplaces were introduced price dispersion between markets increased by about 11-14% but after the introduction of Pan-India electronic auction which further reduced market friction for users, efficiency of markets increased, and price dispersion reduced by about 16%. This is probably because when electronic marketplaces were first introduced it 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), wherein they found that internet-induced reduction in search cost first increased price dispersion on the introduction, and later price dispersion fell in the case of term life insurance markets.

Table 3.4: Effects of electronic marketplace on prices dispersion

	Dependent variable [log$\|P_{jt} - P_{kt}\|$]							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Both markets have electronic marketplace (dummy)	0.141**	0.201***	0.209***	0.138***	0.138***	0.138***	0.138**	0.114*
	(0.054)	(0.049)	(0.049)	(0.046)	(0.053)	(0.020)	(0.068)	(0.069)
Pan India electronic trading (dummy)								-0.271***
								(0.098)
World tea price index † (log)		0.358***	0.354***	0.211***	0.211**	0.211*	0.211*	0.224*
		(0.086)	(0.086)	(0.080)	(0.104)	(0.119)	(0.126)	(0.124)
Absolute arrivals dispersion between markets (log)		0.009	0.012	-0.013	-0.013	-0.013	-0.013	-0.018
		(0.015)	(0.015)	(0.015)	(0.016)	(0.012)	(0.017)	(0.016)
Average rainfall in tea growing regions (log)		0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.012
		(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.022)	(0.023)
Spike in diesel price		0.389	0.398	0.245	0.245	0.245	0.245	0.328
		(0.371)	(0.374)	(0.360)	(0.527)	(0.295)	(0.511)	(0.515)
Lagged absolute price dispersion (t-1) (log)				0.364***	0.364***	0.364***	0.364***	0.379***
				(0.032)	(0.041)	(0.031)	(0.041)	(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
Observations	2,954	2,934	2,934	2,933	2,933	2,933	2,933	3,217
R-squared ᒥᒥ	0.497	0.668	0.676	0.719	0.719	0.719	0.445	0.453

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. In column (1-7), regressions are conducted for the period Jan 2000 to May 2016. Robust standard errors in parentheses (column 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 column (6) and column (7), Driscoll and Kraay standard errors are presented in parentheses to correct for heteroscedasticity, autocorrelation, and contemporary correlation. † World tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices.

ᒥᒥ Column (7) and (8) presents within R-squared

3.7 CONCLUSION AND POLICY IMPLICATIONS

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

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

From a policy perspective, this study has important implications for India. The Government of India introduced the electronic National Agriculture Markets (e-NAM) in 2016 intending to reform existing agriculture marketing systems and to provide producers access to markets across the country through electronic trading. Similar to the electronic marketplace introduced in the tea market, around 1,000 wholesale agriculture markets out of 2,477 markets have been digitised. Our results show that for some agro-based products which are storable for a limited period, transiting from physical to electronic markets can make markets more competitive and efficient. 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, any digital platform that is introduced to connect buyers to sellers needs to ensure that there is a system in place that samples, grades, and values the product sold electronically such that buyers from distant regions can build trust and can purchase commodities electronically without seeing the product. Also, sellers can price discriminate depending on quality.

Before we conclude we acknowledge four limitations of this paper. First, although we have used fixed effect estimation to control for all unobserved time-invariant factors that could be correlated with the decision to transit from physical to the electronic marketplace, we are unable to control for unobserved time-varying factors. Second, given the context of the market we study, the number of cross-sectional units is small, and third, due to the unavailability of data, we are unable to see the overall effect of electronic marketplaces on sales volume and thus comment on whether electronic marketplaces benefit buyers or sellers more.

Future research in this domain should consider analysing: 1. the distribution of payoffs between buyers, sellers, and intermediaries using electronic systems, 2. whether electronic marketplaces enable sellers to access new markets and increase sales, 3. examine the potential externalities created by the users of electronic marketplaces on market actors that do not access such systems, 4. empirically analyse the effects of the increased number of buyers and sellers through electronic marketplaces on prices and 5. study the effects on perishable items such as fruits and vegetables since electronic markets are likely to have different effects on prices depending on the type of commodity.

CHAPTER 4: EFFECTS OF MOBILE PHONES ON RURAL OFF-FARM EMPLOYMENT*

ABSTRACT

Rural poverty remains widespread in many developing countries. Rural households typically depend on agriculture for their livelihoods but often also pursue off-farm economic activities to augment and diversify their incomes. Off-farm income and employment have gained in importance with ongoing structural transformation. However, searching for suitable off-farm employment can be associated with high transaction costs, especially in remote rural areas with poor infrastructure conditions. The increasing spread of mobile phones could help improve access to employment-related information at relatively low costs. Here, we test the hypothesis that ownership of a mobile phone increases rural households' off-farm employment. We use nationally representative panel data from rural India and regression models with household fixed effects and an instrumental variable approach to confirm this hypothesis. Mobile phone ownership significantly increases the likelihood of participating in various types of off-farm employment, including casual wage labour, salaried employment, and non-agricultural self-employment. The effects of mobile phones are significant for all types of rural households but tend to increase with the level of remoteness. Results suggest that mobile phones are effective in improving households' access to off-farm employment, thus contributing to pro-poor rural development and structural transformation.

4.1 INTRODUCTION

Poverty remains widespread in many developing countries, especially in rural areas. Many rural households primarily depend on agriculture for their livelihoods, but the majority of them are also involved in some form of off-farm employment to augment and diversify their income (Amare & Shiferaw, 2017; D'Souza et al., 2020; P. Lanjouw & Murgai, 2009; Reardon et al., 2000; Tsiboe et al., 2016). Traditionally, nonfarm employment was seen as a low productivity sector producing low-quality goods which

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* This essay is co-authored by Matin Qaim. I conceptualized the research, curated the data, developed the methodology, carried out the formal analysis, and wrote the manuscript. Matin Qaim supervised the research, commented at various stages, and edited the manuscript.

were expected to wither over time (Hymer & Resnick, 1969), however, several studies since the early 1970s have emphasized the importance of the sector (Johnston & Kilby, 1975; Mellor & Lele, 1973; Reardon et al., 2000). The role of off-farm employment has been increasing with structural transformation and rising levels of risk in agriculture (Barrett et al., 2001; Bezu et al., 2012; Haggblade et al., 2007; Johnston & Kilby, 1975). In many rural places, off-farm income already accounts for more than 50% of total household income (Babatunde & Qaim, 2010; Bou Dib et al., 2018; Imai et al., 2015). However, finding off-farm employment can be associated with high transaction costs, which is particularly true in remote rural areas where employment opportunities are limited and where public infrastructure is poorly developed. As many rural off-farm jobs are in the informal sector and of relatively short duration, high search costs occur repeatedly and contribute to lower-than-optimal employment rates. Innovations that help to reduce transaction costs could improve households' access to off-farm employment and thus contribute to pro-poor rural development (Aker & Mbiti, 2010). In this article, we analyse whether mobile phones, which reduce the cost of communication and information search, help to increase rural households' off-farm employment.

The past two decades have witnessed a large number of studies on the spread of mobile phones in developing countries and broader economic and social implications. Various studies analyse the effects of mobile phones on agricultural prices and market efficiency (Aker & Fafchamps, 2014; Jensen, 2007; Shimamoto et al., 2015). Other work examines the effects of mobile phones on agricultural productivity, farm performance, and rural household incomes (Abdul-Salam & Phimister, 2017; Aker & Ksoll, 2016; Fan & Salas Garcia, 2018; Fu & Akter, 2016; Kiiza & Pederson, 2012; Lio & Liu, 2006; Muto & Yamano, 2009; Ogutu et al., 2014; Tadesse & Bahiigwa, 2015). A few studies also look at social welfare dimensions such as food security, nutrition, and gender equity (Kalkuhl et al., 2016; Parlasca et al., 2020; Sekabira & Qaim, 2017b), or the role of mobile phones for households' and enterprises' access to financial markets, extension, and related services (Baumüller, 2018; Lashitew et al., 2019; Nakasone et al., 2014; Pellegrina et al., 2017; Tchamyou et al., 2019; Torero & von Braun, 2006). There is also one study that analyses the impact of mobile phones on rural-urban migration (Muto, 2012). While migration is often driven by labour market opportunities, we are not aware of research that explicitly examines the effects of mobile phones on rural off-farm employment.

We address this research gap with household-level panel data from rural India, using the nationally representative Indian Human Development Survey (IHDS). In particular, we analyse the effects of mobile phones on off-farm employment by developing and estimating panel data models with household fixed effects and an instrumental variable approach. We also distinguish between different types of off-farm employment – such as casual wage labour in agriculture and other sectors, salaried employment, and self-employment – as transaction costs and mobile phone effects may differ. For casual and salaried employment, the effects of mobile phones will likely be channelled through reduced transaction costs in finding a job. For self-employment in own non-agricultural enterprises, mobile phones may improve the general business conditions and facilitate communication with clients beyond the local village level. In addition to the average effects of mobile phones, we also estimate heterogeneous effects for households in different locations, hypothesising that the positive employment effects increase with households' physical remoteness. In the regression models, we control for various potential confounding factors that may be jointly correlated with mobile phone ownership and off-farm employment, including informal local communication networks. We also test whether households with larger informal social networks benefit more or less from mobile phone ownership.

The rest of this article is organized as follows. Section 4.2 describes the panel data from rural India and the analytical approaches. Section 4.3 provides a short overview of the role of different off-farm income sources in rural India and the spread of mobile phones during the last 20 years. In section 4.4, the estimation results are presented and discussed, while section 4.5 concludes.

4.2 MATERIALS AND METHODS

4.2.1 DATA

We use panel data from the nationally representative Indian Human Development Survey (IHDS) (Desai & Vanneman, 2005, 2012). The IHDS data were collected in two rounds, namely in 2004-05 and 2011-12. Round-I included 41,554 randomly selected households in 1,503 rural villages and 971 urban neighbourhoods across India. In round-II, 83% (N= 40,018) of the round-I households were re-interviewed and additional 2,134 households were added, resulting in a total round-II sample of 42,152 households. For this study, we use the balanced subsample of rural households included in both rounds, resulting in 54,544 observations from 27,272 households. As will be shown in more detail below, mobile phone ownership of rural households increased considerably between 2005 and 2012, which facilitates our analysis of mobile phone effects on off-farm employment.

4.2.2 GENERAL ANALYTICAL APPROACH

To estimate the impact of household mobile phone ownership on off-farm employment we use panel data regression models of the following type:

$$Y_{it} = \beta_o + \beta_1 M_{it} + \beta_2 X_{it} + u_{it} \tag{1}$$

where Y_{it} is a binary variable indicating whether or not household i was employed in any off-farm activity in year t, M_{it} is a binary variable indicating whether or not the household owned a mobile phone, X_{it} is a vector of control variables that may also influence off-farm employment (e.g., farm size, education, age, remoteness), and u_{it} is a random error term. We are particularly interested in the coefficient estimate β_1. A positive and significant coefficient β_1 would support our general hypothesis that mobile phones increase the likelihood of off-farm employment.

Off-farm employment is defined as any economic activity "off the household's own farm" (Haggblade et al., 2007). It includes casual wage employment in agriculture and other sectors, more formal and regular salaried employment in industry or the services sector, and self-employment in own non-agricultural businesses, such as processing, handicrafts, trading, or other types of services (P. Lanjouw & Murgai, 2009). We estimate equation (1) for all off-farm employments combined and also separately for casual wage employment, salaried employment, and self-employment.

4.2.3 POSSIBLE ENDOGENEITY

If all right-hand-side variables in equation (1) were randomly distributed and correlation between mobile phone ownership (M_{it}) and the error term (u_{it}) could be ruled out, the panel data models could be estimated with a random-effects (RE) estimator. However, since households decide themselves whether they adopt a mobile phone, based on observed and possibly also unobserved characteristics, correlation with the error term is likely and could lead to biased estimates of the coefficient β_1. Under these conditions, the fixed effects (FE) estimator is a better choice because it controls for time-invariant unobserved heterogeneity (Cameron & Trivedi, 2005). We use a FE linear probability model (FE-LPM) specified as follows:

$$Y_{it} = \beta_o + \beta_1 M_{it} + \beta_2 X_{it} + \beta_3 T_t + w_i + u_{it} \tag{2}$$

where T_t is a year dummy variable to control for time fixed effects, and w_i is the household fixed effect. The other variables are defined as above. The errors u_{it} are robust and clustered at the village level to account for possible heteroscedasticity and serial correlation within villages.

While the FE estimator controls for time-invariant unobserved heterogeneity, it does not control for time-variant unobserved heterogeneity or reverse causality. Both aspects are potentially relevant here. Since households with mobile phones are often richer and better educated, they may also be faster in adopting other innovations that may affect their off-farm employment status. To address such potential issues, we use an instrumental variable (IV) approach as a robustness check. Our instrument for household mobile phone ownership is mobile phone adoption at the village level in year t (excluding the household in question). This instrument is time-variant and builds on existing literature demonstrating the important role of informal, community-based social networks for individual technology adoption decisions (Bandiera & Rasul, 2006; Maertens & Barrett, 2012).

A first condition for instrument validity is that the instrument is correlated with household mobile phone ownership (Olea & Pflueger, 2013). This condition is fulfilled, as is shown in Table C.1 in Appendix C. A second condition is that the instrument is not correlated with the outcome variables, other than through household mobile phone ownership. Of course, mobile phone adoption at the village level may be correlated with other village characteristics, such as distance to urban centers, which can also influence off-farm employment. However, in our FE models, we control for other location characteristics so that such factors are not expected to jeopardize instrument validity. Table C.2 in Appendix C shows that the instrument is not significantly correlated with any of the outcome variables, except for salaried employment. Once we control for other covariates, the significant association between the instrument and salaried employment disappears (Table C.3 in Appendix C). Given these test results, we cautiously conclude that the instrument is valid. Using this instrument, we estimate IV-FE-LPM models as a robustness check.

4.2.4 EFFECT HETEROGENEITY

The effects of mobile phone ownership on off-farm employment may vary depending on the household's access to alternative information and communication channels. If a household has good access to employment-related information through channels other than mobile phone communication, the effect of mobile phones may be smaller, whereas poor access to alternative channels may lead to a larger mobile phone effect. We test this hypothesis of heterogeneous effects with FE panel data models of the following type:

$$Y_{it} = \beta_o + \beta_1 M_{it} + \beta_2 X_{it} + \beta_3 Z_{it} + \beta_4 M_{it} \times Z_{it} + \beta_5 T_t + w_i + u_{it} \quad (3)$$

where Z_{it} measures access to alternative information and communication channels. The other variables are defined as above. Here, we are not only interested in the coefficient β_1, but also in the coefficient β_4 for the interaction term between mobile phone ownership (M_{it}) and alternative channels (Z_{it}). A negative and significant estimate for β_4 would confirm the hypothesis that good access to alternative information and communication channels leads to a smaller effect of mobile phones on off-farm employment.

Different alternative channels to obtain employment-related information are conceivable. One important traditional channel for rural households is to travel to urban centers to interact with potential employers and other people. Rural households in locations with short travel times to urban centers have better access to this channel than households located in remoter locations. We measure remoteness in terms of three distance variables, namely distance of the household to the closest tarmac road, distance to closest bus stop, and distance to district capital. As these remoteness variables are correlated, we use each of them in separate estimates of equation (3). Note that longer distances indicate worse access to information so that in these specifications the estimates for β_4 are hypothesized to be positive, that is, we expect remoter households to benefit more from mobile phone ownership.

Another important traditional communication channel involves social interactions at the village level. Neighbours and friends who work in off-farm employment may talk about their experience and also share information about job opportunities within their social network. Such informal local exchange often happens through personal chats rather than mobile phone calls. It can be assumed that villagers involved in a particular type of employment are useful sources of information about this type of employment. Moreover, in India caste plays an important role in social network formation. Hence, we define for each household an employment-related social network ("employment network") in terms of the number of other households in the village belonging to the same caste and being involved in a particular type of off-farm employment. That is, for the salaried off-farm employment model we define the employment network by only counting same-caste village households involved in salaried employment, etc. A larger employment network means better access to relevant information, which might mean that the relative benefits of mobile phone ownership are smaller.

4.3 TRENDS IN OFF-FARM EMPLOYMENT AND THE SPREAD OF MOBILE PHONES

Table 4.1 shows the structure of rural household incomes in India using the 2012 IHDS data (round-II). On average, farm income accounts for only 26% of total income; the rest is off-farm income, including earnings from employment and other off-farm sources such as government transfers, land, and capital rents, etc. Income from employment accounts for about 59% of total household income. Disaggregating the data by expenditure quintiles shows that off-farm income sources are very important for all quintiles, but the off-farm income share is highest for the poorest rural households (Table 4.1). The poorest quintile households are also the ones with the highest share of off-farm employment income, accounting for 67% of their total household income. Casual wage employment in agriculture and other sectors is of particular importance for the poor, stressing that improved access to this type of employment will benefit the poor over-proportionally.

Table 4.1: Structure of household incomes in rural India (2012)

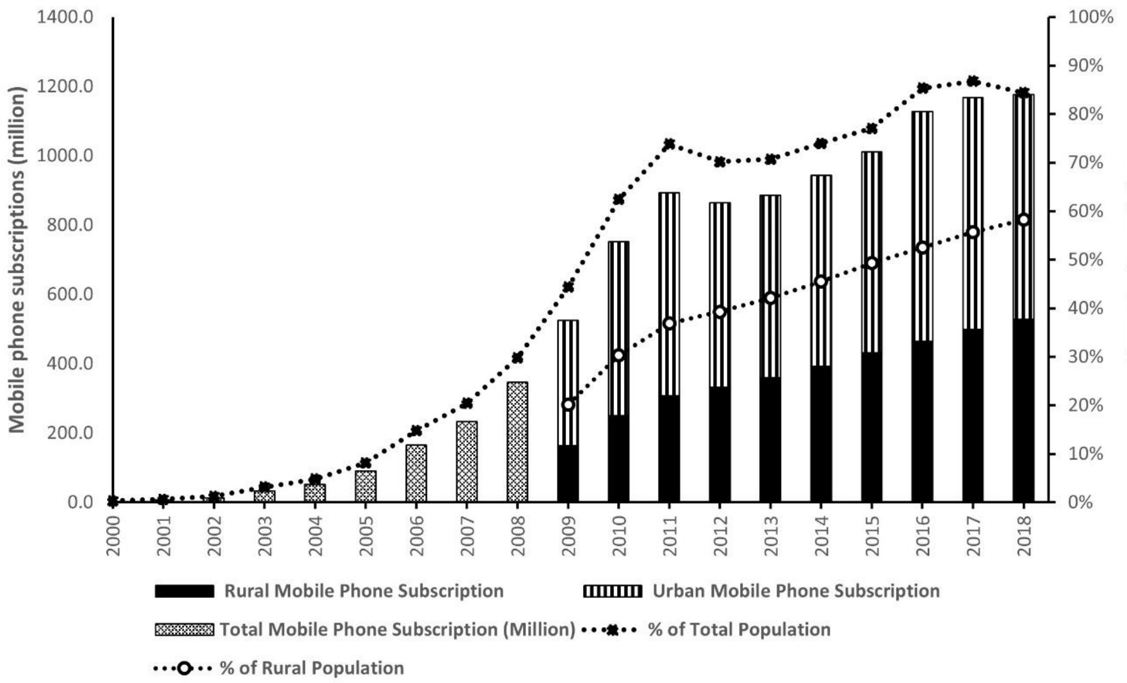
		By expenditure quintile				
Income sources	**All households**	**Poorest 20%**	**2nd quintile**	**3rd quintile**	**4th quintile**	**Richest 20%**
On-farm income	26.2%	21.1%	22.9%	26.5%	28.5%	32.1%
Off-farm income	73.8%	78.9%	77.1%	73.5%	71.5%	67.9%
Casual wage (agriculture)	17.0%	23.6%	20.5%	18.1%	14.4%	8.5%
Casual wage (non-agriculture)	21.9%	30.7%	27.7%	22.9%	17.4%	10.6%
Salaried employment	12.1%	6.9%	8.5%	11.3%	14.7%	19.0%
Self-employment	8.3%	5.5%	7.8%	8.1%	9.5%	10.7%
Other off-farm	14.50%	12.20%	12.60%	13.20%	15.30%	19.20%

Source: Own calculation based on data from IHDS-II.

In terms of mobile phone ownership and use, Figure 4.1 shows trends in India-wide subscription rates over the last 20 years, based on data from the Telecom Regularity Authority of India. In the early 2000s, only 1% of the total population had a mobile phone subscription; this share increased to 86% by 2018. Figure 4.1 also reveals that mobile phones spread rapidly in both urban and rural areas. While adoption rates are higher in urban India, close to 60% of the rural population also had a mobile phone subscription by 2018. Note that the data in Figure 4.1 refer to individuals. When looking at households, mobile phone adoption rates are even higher, because several household members can benefit from the same subscription.

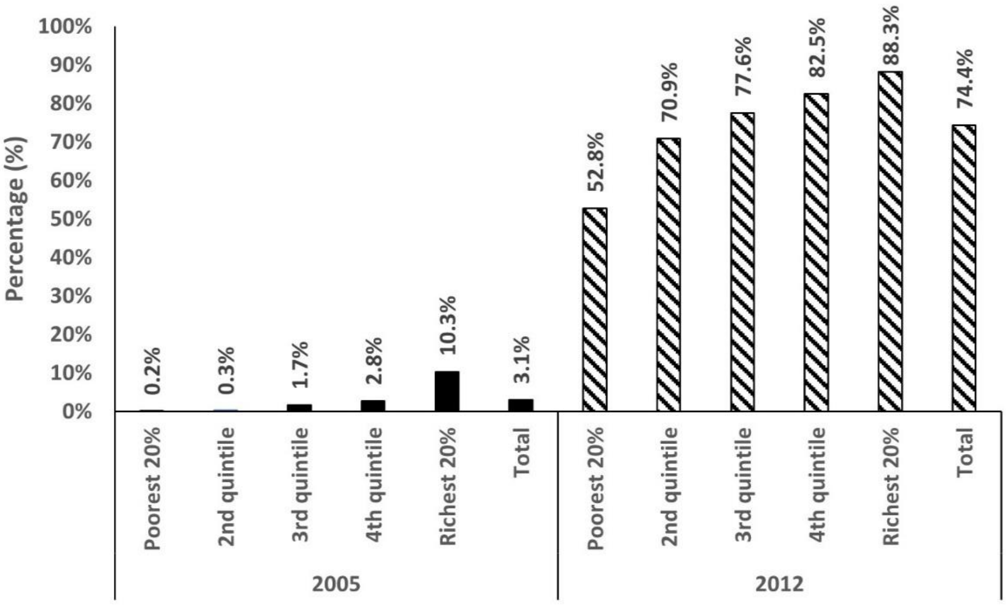
Figure 4.2 shows trends in household-level mobile phone ownership for rural India based on IHDS data, which we use in our econometric analysis. Between 2005 and 2012, mobile phone ownership increased from 3% to 74%. While average adoption rates are higher among the richer households, even in the poorest quintile the adoption rate was 53% already in 2012.

Figure 4.1: Mobile phone expansion in India (2000 to 2018)



Source: Own presentation based on data from Telecom Regulatory Authority of India (TRAI), International Telecommunication Union (ITU), and Census of India 2001 and 2011.

Figure 4.2: Mobile phone ownership in rural households (2005 and 2012)



Source: Own presentation based on data from IHDS-I and IHDS-II.

4.4 EFFECTS OF MOBILE PHONES ON OFF-FARM EMPLOYMENT

4.4.1 DESCRIPTIVE STATISTICS

Table 4.2 presents descriptive statistics of the farm, household, and contextual characteristics that we use as control variables in our regression models, comparing households with and without a mobile phone in 2012 (data for 2005 and the whole sample in both survey rounds are shown in Tables C.4 and C.5 in Appendix C). We see significant differences between the two groups for most of the variables. On average, households with a mobile phone have larger farms, more assets, and higher education levels than households without a mobile phone. Households with mobile phones are also less remote and more likely to have salaried employment or self-employment. Households without a mobile phone are more likely to have casual wage employment.

Table 4.2: Household characteristics by mobile phone ownership (2012)

	With mobile Phone		Without mobile phone			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**SE**
Male household head (dummy)	0.876	0.329	0.804	0.397	0.0720***	0.005
Age of household head (years)	49.217	13.311	50.394	15.567	-1.177***	0.193
Education of household head (years)	8.294	4.626	3.761	4.113	4.532***	0.062
Household size (number)	5.237	2.383	3.917	2.090	1.320***	0.032
Household has BPL ration card (dummy)	0.366	0.482	0.456	0.498	-0.0894***	0.007
Household has APL ration card (dummy)	0.480	0.500	0.277	0.447	0.203***	0.007
Credit in last five years (dummy)	0.613	0.487	0.502	0.500	0.111***	0.007
Household assets (index)	9.920	3.411	6.209	2.453	3.711***	0.044
Cultivated land <2.5 acres (dummy)	0.501	0.500	0.666	0.472	-0.165***	0.007
Cultivated land 2.5-5 acres (dummy)	0.097	0.296	0.093	0.291	0.00427	0.004
Cultivated land 5-10 acres (dummy)	0.119	0.324	0.086	0.280	0.0333***	0.004
Cultivated land >10 acres (dummy)	0.257	0.437	0.136	0.343	0.121***	0.006
Number of livestock (livestock units)	0.655	0.933	0.452	0.732	0.204***	0.012
Distance to tarmac road (km)	0.552	2.661	0.790	3.286	-0.238***	0.040
Distance to closest bus stop (km)	1.878	3.663	2.617	4.723	-0.739***	0.056
Distance to district capital (km)	44.157	31.789	47.882	31.589	-3.726***	0.446
Social group membership (index)	1.545	1.495	1.045	1.115	0.500***	0.020
Employment network (all off-farm)	9.324	7.833	10.349	8.473	-1.025***	0.111
Employment network (casual wage)	6.811	6.487	8.589	7.160	-1.777***	0.092
Employment network (salaried)	2.452	2.784	1.827	2.343	0.625***	0.037
Employment network (self-employed)	1.877	2.610	1.612	2.648	0.265***	0.036
Adoption of mobile phones at village level	0.742	0.155	0.599	0.220	0.144***	0.002
Off-farm employment (dummy)	0.808	0.394	0.801	0.399	0.00697	0.005
Casual wage employment (dummy)	0.569	0.495	0.729	0.445	-0.159***	0.007
Salaried employment (dummy)	0.240	0.427	0.081	0.273	0.159***	0.005
Self-employment (dummy)	0.180	0.384	0.080	0.271	0.0995***	0.005
Observations	20,291		6,981		27,272	

Notes: BPL, below poverty line. APL, above the poverty line. * Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.

The observed differences in the types of employment may – to some extent – be effects of mobile phone ownership but may also simply reflect systematic differences between the two groups that existed even before mobile phones were introduced. We will analyse the effects of mobile phones econometrically below, controlling for possible confounding factors.

4.4.2 AVERAGE EFFECTS

Table 4.3 shows the regression results of the FE-LPM models explained in equation (2) above. Mobile phone ownership has a statistically significant positive effect on off-farm employment. The estimates in column (1) of Table 4.3 suggest that mobile phone ownership increases the probability of off-farm employment by 3.9 percentage points. The other columns in Table 4.3 show significantly positive effects of mobile phones also in the separate models for different employment types. Interestingly, the effect magnitude is larger for casual wage employment (column 2) than for salaried employment (column 3) and self-employment (column 4). This is plausible: casual employment is typically not very stable, meaning that job searches with high transaction costs are necessary more frequently. These transaction costs can be reduced through ownership and the use of a mobile phone.

Table 4.3: Effects of mobile phone ownership on off-farm employment (FE-LPM models)

	(1) Off-farm employment (dummy)		(2) Casual wage employment (dummy)		(3) Salaried employment (dummy)		(4) Self-employment (dummy)	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Mobile phone (dummy)	0.0389***	(0.0064)	0.0409***	(0.0070)	0.0317***	(0.0067)	0.0210***	(0.0058)
Male head (dummy)	0.1310***	(0.0103)	0.0787***	(0.0104)	0.0422***	(0.0097)	0.0393***	(0.0079)
Age of head (years)	-0.0019***	(0.0002)	-0.0012***	(0.0003)	-0.0001	(0.0002)	0.0003	(0.0002)
Education of head (years)	0.0070***	(0.0008)	0.0000	(0.0008)	0.0109***	(0.0008)	0.0020***	(0.0006)
Household size (number)	0.0151***	(0.0012)	0.0154***	(0.0015)	0.0073***	(0.0013)	0.0062***	(0.0012)
BPL ration card (dummy)	0.0091	(0.0056)	0.0265***	(0.0068)	-0.0109*	(0.0064)	0.0040	(0.0057)
APL ration card (dummy)	-0.0022	(0.0064)	-0.0021	(0.0076)	-0.0067	(0.0063)	0.0111*	(0.0060)
Credit (dummy)	0.0233***	(0.0043)	0.0303***	(0.0050)	0.0126***	(0.0048)	0.0211***	(0.0045)
Household assets (index)	-0.0060***	(0.0012)	-0.0185***	(0.0014)	0.0041***	(0.0011)	0.0109***	(0.0011)
Social group membership	0.0092***	(0.0018)	0.0030	(0.0020)	0.0079***	(0.0018)	0.0061***	(0.0017)
Land <2.5 acres (dummy)	0.0589***	(0.0080)	0.0447***	(0.0085)	0.0207***	(0.0073)	0.0079	(0.0071)
Land 2.5-5 acres (dummy)	-0.0034	(0.0098)	-0.0032	(0.0102)	0.0072	(0.0084)	-0.0025	(0.0082)
Land 5-10 acres (dummy)	-0.0107	(0.0098)	-0.0096	(0.0097)	0.0091	(0.0079)	-0.0132*	(0.0076)
Number of livestock	-0.0208***	(0.0034)	-0.0168***	(0.0032)	-0.0047*	(0.0026)	-0.0098***	(0.0028)
Employment network	0.0364***	(0.0015)	0.0392***	(0.0016)	0.0344***	(0.0020)	0.0406***	(0.0020)
Distance to district capital	0.0000	(0.0001)	0.0002	(0.0001)	-0.0000	(0.0001)	-0.0002	(0.0001)
Year 2012 (dummy)	-0.0016	(0.0054)	0.0268***	(0.0057)	-0.0239***	(0.0053)	-0.0308***	(0.0053)
Constant	0.2921***	(0.0235)	0.2925***	(0.0239)	-0.0810***	(0.0206)	-0.1087***	(0.0179)
Observations	53,160		53,160		53,160		53,160	
F-statistic	141.04***		137.24***		90.08***		125.19***	
Hausman test, chi-squared	2440.48***		2491.68***		431.72***		6698.72***	

Notes: Standard errors are robust and cluster-corrected at the village level. * Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.

The control variables in Table 4.3 suggest that household size, male household head, and longer education have significantly positive effects on off-farm employment. Education is particularly relevant for salaried employment and self-employment, as these employment types tend to require more skills and human capital. Farm characteristics also matter as one would expect: households with little land and few animals are more likely to be involved in off-farm employment than households with more extensive farming activities. We also control for employment networks as alternative communication channels at the village level. Unsurprisingly, larger employment networks significantly increase the probability of off-farm employment, which is true for all employment types. The year dummy shows an interesting pattern: in 2012, more households were employed in casual jobs but fewer households had salaried employment and self-employment than in 2005. This points to a decrease in more stable and lucrative off-farm opportunities over time.

As a robustness check, the IV-FE estimates are shown in Table C.6 in Appendix C. As in Table 4.3 without IV, mobile phone ownership has significantly positive effects on off-farm employment and also on all types of off-farm employment. These are reassuring results, implying that possible issues with time-variant unobserved heterogeneity or reverse causality do not change our main results. Interestingly, the magnitude of the effects of mobile phone ownership is larger in the IV models than in the FE effects models without IV. Hence, for our interpretation, we rely on the more conservative results without IV.

4.4.3 HETEROGENEOUS EFFECTS

We now analyse whether the effects of mobile phones on off-farm employment differ by households' access to alternative information and communication channels, as explained in section 4.2.2. Table 4.4 presents the regression results of equation (3), using interaction terms between mobile phone ownership and different measures of remoteness in addition to the other controls. In the model in column (1) of Table 4.4, we use distance to the closest bus stop as the measure of remoteness, in column (2), we use distance to the closest tarmac road, in column (3) distance to the district capital. In columns (1) and (2), the interaction terms are positive and statistically significant, implying that the effects of mobile phone ownership on off-farm employment increase with the level of remoteness. This is a welcome finding from a social perspective, confirming our hypothesis that remoter households with less access to alternative information and communication channels benefit more from mobile phones.

Table 4.4: Effects of mobile phones on off-farm employment by remoteness (FE-LPM models)

	(1) Off-farm employment		(2) Off-farm employment		(3) Off-farm employment	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Mobile phone (MP, dummy)	0.0352***	(0.0065)	0.0382***	(0.0065)	0.0388***	(0.0077)
Distance to closest bus stop (km)	-0.0001	(0.0007)				
MP x Distance to closest bus stop	0.0020**	(0.0009)				
Distance to tarmac road (km)			0.0002	(0.0005)		
MP x Distance to tarmac road			0.0019*	(0.0011)		
Distance to district capital (km)					0.0000	(0.0001)
MP x Distance to district capital					0.0000	(0.0001)
Male household head (dummy)	0.1325***	(0.0104)	0.1333***	(0.0104)	0.1310***	(0.0103)
Age of household head (years)	-0.0019***	(0.0002)	-0.0019***	(0.0002)	-0.0019***	(0.0002)
Education of head (years)	0.0070***	(0.0008)	0.0071***	(0.0008)	0.0070***	(0.0008)
Household size (number)	0.0147***	(0.0012)	0.0149***	(0.0012)	0.0151***	(0.0012)
BPL ration card (dummy)	0.0092	(0.0057)	0.0104*	(0.0057)	0.0091	(0.0056)
APL ration card (dummy)	-0.0016	(0.0064)	-0.0002	(0.0065)	-0.0022	(0.0064)
Credit (dummy)	0.0234***	(0.0043)	0.0230***	(0.0043)	0.0233***	(0.0043)
Household assets (index)	-0.0061***	(0.0012)	-0.0061***	(0.0013)	-0.0060***	(0.0012)
Social group membership	0.0097***	(0.0018)	0.0090***	(0.0018)	0.0092***	(0.0018)
Land <2.5 acres (dummy)	0.0602***	(0.0082)	0.0622***	(0.0083)	0.0589***	(0.0080)
Land 2.5-5 acres (dummy)	-0.0007	(0.0100)	0.0017	(0.0101)	-0.0034	(0.0099)
Land 5-10 acres (dummy)	-0.0088	(0.0099)	-0.0062	(0.0100)	-0.0107	(0.0098)
Number of livestock (units)	-0.0203***	(0.0035)	-0.0200***	(0.0035)	-0.0208***	(0.0034)
Employment network	0.0358***	(0.0015)	0.0360***	(0.0015)	0.0364***	(0.0015)
Year 2012 (dummy)	-0.0022	(0.0055)	-0.0018	(0.0056)	-0.0016	(0.0054)
Constant	0.2964***	(0.0229)	0.2910***	(0.0231)	0.2921***	(0.0239)
Observations	52,620		52,317		53,160	
F-statistic	129.16***		127.31***		133.2***	
Hausman test, chi-squared	2385.19***		2292.3***		2443.72***	

Notes: Standard errors are robust and cluster-corrected at the village level. * Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.

The interaction of mobile phone ownership and distance to the district capital in column (3) of Table 4.4 is not statistically significant. However, further disaggregation by type of employment reveals a significant positive interaction term for casual wage employment (Table C.7 in Appendix C), which is particularly relevant for the poorest rural households. As mentioned, casual wage employment tends to involve more frequent job searches than the other employment types. For the other two employment types (salaried and self-employment), negative interaction terms are observed in Table C.7 in Appendix C.

Next, we analyse whether the effects of mobile phones differ by the size of the households' local employment network at the village level, again with interaction terms as explained in equation (3). The interaction terms between mobile phone ownership and local employment networks are negative but insignificant in columns (1) and (3) of Table 4.5. However, for casual wage employment (column 2) and self-employment (column 4) the interaction terms are negative and significant, suggesting that access to a larger local employment network reduces the employment effects of mobile phone ownership. These results also confirm our hypothesis that households with poor access to alternative information and communication channels benefit over-proportionally from mobile phones.

Table 4.5: Effects of mobile phones on off-farm employment by employment network (FE-LPM models)

	(1) Off-farm employment		(2) Casual wage employment		(3) Salaried employment		(4) Self-employment	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Mobile phone (MP, dummy)	0.0403***	(0.0076)	0.0499***	(0.0077)	0.0361***	(0.0074)	0.0274***	(0.0070)
Employment network	0.0364***	(0.0016)	0.0400***	(0.0015)	0.0347***	(0.0022)	0.0419***	(0.0016)
MP x Employment network	-0.0001	(0.0005)	-0.0013**	(0.0006)	-0.0019	(0.0019)	-0.0036*	(0.0020)
Male head (dummy)	0.1310***	(0.0103)	0.0788***	(0.0104)	0.0421***	(0.0097)	0.0394***	(0.0079)
Age head (years)	-0.0019***	(0.0002)	-0.0012***	(0.0003)	-0.0001	(0.0002)	0.0003	(0.0002)
Education head (years)	0.0070***	(0.0008)	0.0000	(0.0008)	0.0109***	(0.0008)	0.0020***	(0.0006)
Household size (number)	0.0151***	(0.0012)	0.0154***	(0.0015)	0.0073***	(0.0013)	0.0061***	(0.0012)
BPL ration card (dummy)	0.0090	(0.0056)	0.0263***	(0.0068)	-0.0111*	(0.0064)	0.0043	(0.0057)
APL ration card (dummy)	-0.0023	(0.0064)	-0.0025	(0.0076)	-0.0069	(0.0063)	0.0114*	(0.0060)
Credit (dummy)	0.0233***	(0.0043)	0.0301***	(0.0050)	0.0127***	(0.0048)	0.0211***	(0.0045)
Household assets (index)	-0.0060***	(0.0012)	-0.0184***	(0.0014)	0.0042***	(0.0011)	0.0110***	(0.0011)
Social group membership	0.0092***	(0.0018)	0.0030	(0.0020)	0.0079***	(0.0018)	0.0060***	(0.0017)
Land <2.5 acres (dummy)	0.0589***	(0.0080)	0.0445***	(0.0085)	0.0210***	(0.0073)	0.0081	(0.0071)
Land 2.5-5 acres (dummy)	-0.0033	(0.0098)	-0.0030	(0.0102)	0.0074	(0.0084)	-0.0025	(0.0082)
Land 5-10 acres (dummy)	-0.0107	(0.0098)	-0.0095	(0.0097)	0.0091	(0.0079)	-0.0134*	(0.0076)
Number of livestock (units)	-0.0208***	(0.0034)	-0.0168***	(0.0032)	-0.0047*	(0.0026)	-0.0098***	(0.0028)
Distance district capital (km)	0.0000	(0.0001)	0.0002	(0.0001)	-0.0000	(0.0001)	-0.0002	(0.0001)
Year 2012 (dummy)	-0.0017	(0.0054)	0.0265***	(0.0057)	-0.0240***	(0.0053)	-0.0304***	(0.0052)
Constant	0.2916***	(0.0238)	0.2880***	(0.0235)	-0.0815***	(0.0207)	-0.1106***	(0.0177)
Observations	53,160		53,160		53,160		53,160	
F-statistic	133.21***		129.93***		85.21***		118.76***	
Hausman test, chi-squared	2441.81***		2496.26***		426.44***		343.94***	

Notes: Standard errors are robust and cluster-corrected at the village level. * Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.

4.5 CONCLUSION AND POLICY IMPLICATIONS

While rural households often heavily depend on farming for their livelihoods, off-farm income sources have also gained in importance and will continue to do so with the ongoing structural transformation observed in many developing countries. However, rural labour markets are often not functioning well due to high transaction costs involved in job searches. This is especially true in remote rural areas with poor infrastructure conditions and weak institutions. In this article, we have tested the hypothesis that mobile phones improve rural households' access to off-farm employment by reducing transaction costs and improving communication with potential employers, business partners, and other relevant persons for job searches. Using representative panel data from households in rural India, this hypothesis was confirmed. Mobile phone ownership significantly increases households' participation in off-farm employment, also after controlling for possible confounding factors. Positive effects of mobile phones were shown for off-farm employment in general and also for all sub-categories of off-farm employment, including casual wage labour in agriculture and other sectors, salaried employment, and self-employment in small non-agricultural businesses.

The data from rural India show that off-farm income already accounts for 74% of total household income and is most relevant for the poorest households with small agricultural landholdings. Poor households depend primarily on casual wage employment, involving unstable jobs and repeated job searches. Mobile phone ownership had the largest positive effects on participation in casual wage employment. We also analysed the role of alternative information and communication channels, including social networks at the village level and proximity to infrastructure and urban centers. Mobile phones have the largest positive effects on off-farm employment for households with low access to alternative channels, namely those in remote locations and with small social networks at the village level. These results suggest that mobile telephony can support pro-poor rural development and structural transformation.

Our findings also have important policy implications. Of course, mobile phones should not be seen as a substitute for other mechanisms to improve rural households' access to off-farm employment, including, but not limited to, improved road infrastructure, education, and support of labour-intensive rural enterprises. However, ensuring that all households – including those located in remote and disadvantaged regions – have good and affordable access to mobile technologies and networks can reduce transaction costs and thus improve labour market efficiency, as our estimates demonstrate.

Our study is the first to explicitly analyse the effects of mobile phones on rural off-farm employment. Follow-up research in other countries and regions and possibly also with a focus on other relevant issues – such as gender equity in employment, wages, or job quality – will be important to further advance our knowledge on the relationship between mobile phones and rural employment.

CHAPTER 5: EFFECTS OF MOBILE PHONES ON WOMEN'S MOBILITY AND ACCESS TO REPRODUCTIVE HEALTHCARE SERVICES IN INDIA*

ABSTRACT

Women's economic and social empowerment is facilitated by their ability to move around independently and safely. However, in many developing countries female mobility is restricted by patriarchal codes of conduct, structural impediments related to poor quality of roads and transport systems, and security issues. Mobile phones could help to better connect women to information and social networks, strengthen their bargaining power within households, and thus also increase their mobility and access to public services. Here, we use nationally representative data from India to analyse the effects of women's mobile phone use on their physical mobility and access to reproductive healthcare services. Issues of endogeneity are addressed through an instrumental variable approach. Results confirm that women's mobile phone use has positive and significant effects on both outcomes. Further disaggregation shows that the positive effects are particularly large for women from households below the poverty line. Even women from conservative households and communities where veiling and gender seclusion are required benefit from mobile phones. These findings suggest that mobile phone use among women contributes to female empowerment with positive social welfare implications.

5.1 INTRODUCTION

Women's economic and social empowerment is facilitated by their ability to move around independently and safely. However, in many developing countries women and girls are restricted in their mobility by religious norms, class-hierarchies, cultural expectations, and tasks to perform within the household. Many of these social and cultural norms persists because women experience disproportionally higher costs of information than men. Costly and asymmetric information isolate women economically

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* This essay is co-authored by Matin Qaim. I conceptualized the research, curated the data, developed the methodology, carried out the formal analysis, and wrote the manuscript. Matin Qaim supervised the research, commented at various stages, and edited the manuscript..

and socially, which affects the optimal utilization of resources women control, their access to outside options, and exposes them to higher levels of risks (Fletschner & Mesbah, 2011). Furthermore, structural barriers, such as inadequate infrastructure and transport systems, and security concerns, including the fear of sexual harassment, often seclude women from public spaces. Such mobility constraints can also have serious negative implications for women's ability to access education, healthcare services, and employment (Amin 1997; Balk 1994; Duflo 2012; Dyson and Moore 1983; Klasen 2018). The increasing spread of mobile phones in many developing countries could help to overcome some of these constraints and better connect women to social networks, markets, and public services. Better access to information and knowledge may also increase women's independence and decision-making power within the household (Kabeer 1999). Here, we analyse whether women's use of mobile phones increases their mobility and access to reproductive healthcare services.

A broad body of literature has analysed the effects of mobile phones on market access and efficiency as well as on income and other dimensions of economic welfare in various developing countries (Aker, 2010; Aker & Fafchamps, 2014; Aker & Ksoll, 2016; Beuermann et al., 2012; Fu & Akter, 2016; Jensen, 2007; Muto, 2012; Muto & Yamano, 2009; Parlasca et al., 2020; Shimamoto et al., 2015; Tadesse & Bahiigwa, 2015; Torero & von Braun, 2006). However, there are hardly any empirical studies that have looked at mobile phone effects through a gender lens. We are aware of only one study that has examined gendered effects of mobile phones, namely Sekabira and Qaim (2017) who showed that mobile phone use is positively associated with female financial autonomy in rural households in Uganda. Sekabira and Qaim (2017) did not analyse the effects of mobile phones on women's mobility and access to reproductive healthcare services. This research gap is addressed here with micro-level data from India.

In particular, we use nationally representative data from the Indian Human Development Survey (IHDS) to analyse the effects of mobile phone use on a female physical mobility index and the use of contraceptive methods. India is an interesting example for this analysis because in large parts of the Indian society traditional patriarchal codes of conduct still prevail. Potential issues of endogeneity in our empirical analysis are addressed with an instrumental variable approach. In addition to the average effects of mobile phone use for all women, we also examine heterogenous effects for women from households above and below the poverty line and with and without traditional female seclusion requirements. Such effects of mobile phones were not analysed previously, neither in India nor elsewhere. Hence, the findings may offer interesting new insights with direct relevance for development policy.

5.2 CONCEPTUAL FRAMEWORK

In South Asia, it is common practice for women to seclude themselves from public spaces due to social norms that put a high moral value on female "honour" and safety from sexual harassment and violence (Jayachandran, 2015). As a symbolic gesture of seclusion, women often cover their faces and bodies in front of people outside their families. The practice of veiling is called the "purdah" system.[7] In its most extreme form, purdah involves complete segregation between men and women and the prohibition of women to leave the premises of their home. In less extreme forms, women are required to cover their face and body post-puberty or post-marriage, and mobility outside the house is permitted when accompanied by a male family member. In modern India, not all households follow the traditional purdah system. The specific boundary where a woman can move and function independently often varies by economic status and the household's place in the caste hierarchy (Bennett, 1992).

Restrictions on female mobility directly affect women's economic and social participation but can also have wider negative implications for women's access to healthcare services. The maternal mortality rate — an important healthcare indicator— is higher in India than it is in many other countries with similar mean income levels (WDI, 2021). Around two-thirds of all maternal mortality in India is due to bleeding and infection after childbirth, high blood pressure in the course of pregnancy, and complications from delivery and unsafe abortions. Further, unintended pregnancies are the primary cause of death amongst adolescent girls. Preventive healthcare interventions include improved information about family planning and better access to contraceptive methods. However, cultural norms and physical mobility restrictions for women can lead to low use of contraceptives, especially in traditional households.

Mobile phones can affect women's physical mobility and access to healthcare services through different pathways. First, mobile phones may assure households that they can connect with their female member, even if she leaves the house alone, thus relieving safety concerns, which are often an important reason for restricted female mobility. Second, and relatedly, mobile phones may also give women a sense of personal safety when leaving their home without male company. Third, mobile phones can be an important device to access information about various topics, including reproductive

[7] Purdah means curtain in Hindi and is the general term used for all forms of veiling in the local context. Various forms of veiling exist where women cover either their face or their whole body, including Ghungat, Burkha, Purdah, or Pallu (Bennett, 1992; Papanek, 1973).

health and contraceptive methods. Such information can come through official information campaigns, which sometimes use mobile phone-based text messages for distribution, or through individual communication with social networks and/or healthcare workers.

A more indirect mechanism is that mobile phones may also improve women's bargaining power within the household and thus their ability to negotiate more freedom, including more autonomy in terms of physical mobility and a greater say in family planning decisions. The literature on intra-household bargaining shows that women's bargaining power increases with credible thread points (Lundberg & Pollak, 1993; Manser & Brown, 1980; McElroy & Horney, 1981). Threat points are not only influenced by individual control over financial resources but also depend on access to knowledge and information, bargaining skills, and the ability to mobilize interpersonal networks (Fafchamps et al., 2009; Fletschner & Mesbah, 2011; McElroy, 1990). Mobile phones could play an important role for women in this respect, especially in the context of India where women's physical mobility is often restricted due to cultural norms. In addition to better access to information, greater ability to communicate with natal family and friends, even over longer distances, may increase women's self-confidence and thus their threat points and intra-household bargaining power.

5.3 MATERIALS AND METHODS

5.3.1 DATA

We use the second round of the nationally representative Indian Human Development Survey (IHDS-II), which was conducted in 2011-12 (Desai & Vanneman, 2012). Unlike the first round of IHDS, which was conducted in 2004-05, the second round includes individual-level data on mobile phone usage, which is required for our analysis. That is, we are not only interested in whether or not a household owns one or several mobile phones but whether individual women in the household actually use a mobile phone.

In IHDS-II, interviews were conducted with over 42,000 households in rural and urban areas. For the analysis, we use the individual, household, and eligible women datasets. The study uses a sample of 39,523 ever-married women interviewed in the eligible woman dataset. 'Eligible' women are defined as, married women in the age group of 15-49. The sample for the analysis also includes women above the age of 49 who were already interviewed in the first round of the survey conducted in 2004-05[8]. In most households, data from one eligible woman were collected; for a few households, data from more than one woman are available and included in the analysis. The data include information on various sociodemographic household characteristics as well as on individual-level education, mobility, health, fertility, family planning, empowerment, and mobile phone use. Hence, the data are suitable to study the effects of women's mobile phone use on their mobility and access to reproductive healthcare services.

5.3.2 MEASUREMENT OF OUTCOME VARIABLES

The two outcomes of interest in this study are women's physical mobility and their access to reproductive healthcare services. Physical mobility is measured through an index that we construct by using women's answers to seven different binary survey questions. These questions are: (i) Can you visit health clinics alone? (ii) Can you visit relatives or friends at their home alone? (iii) Can you visit a grocery store alone? (iv) Can you travel a short distance by train or bus alone? (v) Have you been to a village, town, or city besides your current residence during the last 5 years? (vi) Have you been to another state during the last 5 years? (vii) Have you been abroad during the last 5 years?

For the construction of the index, we calculate the unweighted average of all seven 0/1 answers for each woman. Hence, the mobility index ranges from 0 to 1, with higher values indicating higher physical mobility. The same approach of averaging over several binary variables was used previously to create indexes of women's autonomy (Eswaran & Malhotra, 2011; Jensen & Oster, 2009).

To measure women's access to reproductive healthcare services, we employ individual use of contraceptive methods for family planning as a proxy variable. Contraceptives allow women to decide when and how many children to have. Especially in the Indian context, family planning services are also considered an important public health intervention to reduce infant and maternal mortality. For our analysis, we use a binary variable indicating whether or not the individual woman used any form of contraception to delay or prevent pregnancy at the time of the survey.

[8] We use all 39,523 observations of eligible women in 2011-12 whenever possible, but due to missing data for some of the variables, the effective sample for the different regressions is somewhat smaller in certain cases.

5.3.3 Regression models

To estimate the effects of women's mobile phone use on the two outcome variables we estimate regression models of the following type:

$$Y_{ij} = \beta_o + \gamma_1 MP_{ij} + \beta_1 X_{ij} + \beta_2 H_{ij} + \delta_1 D_j + \varepsilon_{ij} \tag{1}$$

where Y_{ij} is the respective outcome for woman *i* living in village *j*. We estimate separate regressions for the mobility index and access to reproductive healthcare services (use of contraceptive methods). The main explanatory variable of interest is MP_{ij}, which is a binary variable indicating whether or not women *i* uses a mobile phone. A positive and significant coefficient γ_1 would confirm our hypothesis that mobile phone use increases women's mobility and access to reproductive healthcare services.

In the regression models, we control for confounding variables that may jointly influence mobile phone use and the outcomes, including individual characteristics of the woman, X_{ij}, such as age, education, or mother's education, as well as household characteristics, H_{ij}, such as household size, caste, asset ownership, and sex, age, and education of the household head. We also control for socioeconomic status by including a dummy variable for the household's ownership of a BPL (below poverty line) ration card. Further, we control for regional differences through a vector of district fixed effects D_j. ε_{ij} in equation (1) is a random error term with mean zero. We cluster standard errors at the village level. In robustness checks, we also cluster standard errors at the household level.

5.3.4 Dealing with endogeneity

As mentioned, to test our main hypothesis that mobile phone use has positive effects on women's physical mobility and access to reproductive healthcare services we are particularly interested in the estimate of γ_1 in equation (1). However, women's mobile phone use is not randomly allocated but likely influenced by several observed and also unobserved factors. This means that MP_{ij} may be correlated with the error term ε_{ij}, which can lead to endogeneity bias in the estimation of γ_1. We use an instrumental variable (IV) approach to reduce such bias. The IV approach requires an instrumental variable Z_{ij}, which is correlated with M_{ij}, uncorrelated with ε_{ij}, and has no direct effect on the outcome variables Y_{ij} (Wooldridge, 2010).

Our instrument builds on the fact that social networks at the local level play an important role in the adoption of innovations (Bandiera & Rasul, 2006; Maertens & Barrett, 2012). In particular, we employ mobile phone use by a woman's local peer group as an instrument for her own use of mobile phones. The peer group here is defined as women in the same age group within the village. That is, our instrument measures the number of women in the same village and age group using a mobile phone, excluding the respondent herself and other women in her own household.[9] In the Indian context, age-specific peer groups are particularly relevant, as intimate conversations between different generations are often limited due to social traditions.

We carry out different tests of instrument validity. The first stage regression results of the IV models are shown in Table D.1 in Appendix D. They confirm the instrument relevance, that is, the likelihood of a woman using a mobile phone increases significantly with more mobile phone users in her peer group. The second criterion for a valid instrument is that it is not correlated with the outcome variables, other than through the use of mobile phones. We test possible correlations between our instrument and both outcome variables in Table D.2 in Appendix D. The size of the peer group using mobile phones is not significantly correlated with women's mobility or the use of contraceptives, suggesting that the instrument is valid. Table D.1 in Appendix D also reports Durbin χ^2 and Wu-Hausman F statistics, testing the endogeneity of mobile phone use in equation (1). The null hypothesis is that mobile phone use is exogenous. Based on both tests, we reject this null hypothesis, concluding that using the IV approach is important to reduce issues of endogeneity bias.

Despite our tests suggesting instrument validity, the IV approach alone may not fully solve potential issues of unobserved heterogeneity. Hence, we carry out robustness checks by including additional control variables in equation (1) that could proxy for remaining unobserved factors jointly influencing mobile phone use and the outcome variables. First, we include a set of variables capturing various components of women's autonomy (financial autonomy, agency, etc.). Second, we include a set of variables capturing women's access to alternative sources of information, such as radio, TV, and newspapers. More details of these additional sets of control variables are provided in Tables D.3 and D.4 in Appendix D. Note that these controls may possibly be endogenous themselves when included in equation (1). However, this is not of concern in our robustness checks, because – rather than interpreting the coefficients of these additional controls – we want to see to what extent the mobile phone effects change after their

[9] We use the following age groups: 15-22 years, 23-30 years, 31-40 years, 41-50 years, 51-60 years.

inclusion. No major changes would imply that the estimated mobile phone effects are robust to unobserved heterogeneity.

5.3.5 SUBSAMPLE ANALYSES

To identify the average effects of mobile phones on the two outcome variables, the regression models are estimated with the full sample of women. In addition to these average effects, we are also interested to better understand possible heterogeneity in mobile phone effects across different groups of women. Therefore, we estimate the IV models for different subsamples, namely (i) women from households below and above the poverty line, and (ii) women from households practicing and not practicing the purdah system (gender seclusion, see section 5.2 for more details).

Poverty in the IHDS-II data is defined based on monthly per capita consumption expenditures and official cut-offs specific for each state and differentiating between rural and urban areas. In the total women sample, around 17% are from households that are categorized as poor and 58% are from households that practice the purdah system (Table 5.1).

Table 5.1: Number of observations

	Number of observations	**Percentage**
Total sample of women	39,523	100.00
Poor	6,795	17.20
Non-poor	32,719	82.80
Purdah	23,031	58.27
Non-purdah	16,492	41.73

Source: Own calculations based on data from IHDS-II.

5.4 RESULTS AND DISCUSSION

5.4.1 DESCRIPTIVE STATISTICS

Table 5.2 presents the summary statistics of the key outcome and explanatory variables. The first row shows results for the whole sample of women, whereas the other rows show mean values for the different subsamples. Around 43% of all women used a mobile phone in 2011-12. As expected, this proportion is lower for women from poor households than for women from non-poor households. Differences in mobile phone use are also observed between women from households practicing and not practicing the purdah system, but interestingly even in households practicing purdah around 40% of the women use a mobile phone.

Table 5.2: Summary statistics of key variables

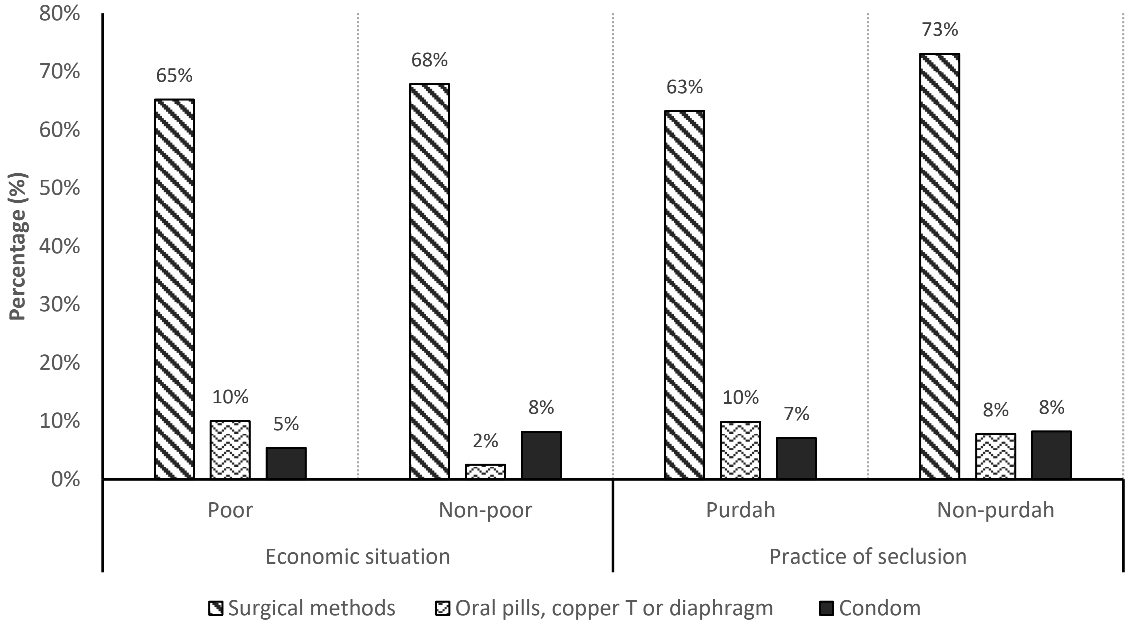
	(1) Mobile phone use (dummy)	(2) Women's mobility (index, 0-1)	(3) Use of contraceptives (dummy)
Total sample of women	0.435	0.549	0.738
	(0.495)	(0.227)	(0.439)
Poor	0.271	0.514	0.729
	(0.445)	(0.217)	(0.444)
Non-poor	0.470	0.556	0.741
	(0.499)	(0.229)	(0.438)
Purdah	0.403	0.536	0.7234
	(0.491)	(0.231)	(0.447)
Non-purdah	0.482	0.567	0.760
	(0.499)	(0.221)	(0.426)

Note: Mean values are shown with standard deviations in parentheses.

Columns (2) and (3) of Table 5.2 show sample mean values of the outcome variables. The mean mobility index of 0.55 for the whole sample means that on average only 55% of the different mobility questions were answered positively by the female respondents. Unsurprisingly, women in poor and purdah-practicing households are more restricted in their mobility than their counterparts in non-poor and non-purdah households. In terms of reproductive healthcare, 74% of all women use any contraceptive methods, again with certain differences across the subsamples.

Figure 5.1 provides further insights into the use of different contraceptive methods in India. Of all women who used contraceptives at the time of the survey, two-thirds had undergone female sterilization or hysterectomy, 9% used oral pills, copper T, or diaphragm, and 8% used condoms. India has a long history of female sterilization as the main method of contraception to reduce fertility and population growth (Visaria et al., 1999). Figure 5.1 shows that in poor and traditional households following the purdah system, rates of female sterilisation are somewhat higher than the full sample average.

Figure 5.1: Contraceptive use by women in India



Source: Own presentation based on data from IHDS-II.

Table 5.3 presents descriptive statistics of outcome and control variables used in the regression analysis, disaggregated by mobile phone use. Women using a mobile phone have significantly higher mobility and are more likely to use contraceptives than women not using a mobile phone. This is in line with our general hypothesis. However, there are also significant differences in terms of many other socioeconomic variables, so that these descriptive comparisons should not be overinterpreted in a causal sense.

Women using a mobile phone are younger and better educated; they are also more likely to have educated mothers and a literate spouse than women not using a mobile phone. There are also significant differences in terms of household asset ownership and caste. Households with women not using a mobile phone are more likely to be from disadvantaged groups, including Scheduled Castes (SC), Scheduled Tribes (ST), and other backward castes (OBC). All these variables point at systematic differences between the groups, which we control for in the regression models below.

Table 5.3: Descriptive statistics for women using and not using a mobile phone

	(1) Uses a mobile phone		(2) Does not use a mobile phone			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**SE**
Mobility (index)	0.582	0.228	0.524	0.225	0.058***	0.002
Uses contraceptives (dummy)	0.764	0.424	0.719	0.450	0.045***	0.005
Age of respondent (number)	35.008	9.274	37.361	10.181	-2.353***	0.099
Primary education (dummy)	0.344	0.475	0.301	0.459	0.043***	0.005
Secondary education (dummy)	0.217	0.412	0.118	0.323	0.099***	0.004
Higher education (dummy)	0.112	0.315	0.035	0.185	0.076***	0.003
Graduate and above (dummy)	0.123	0.329	0.022	0.147	0.101***	0.002
No formal education (dummy)	0.203	0.403	0.523	0.499	-0.319***	0.005
Mother's education (number)	2.267	3.645	0.885	2.323	1.382***	0.030
Spouse is literate (dummy)	0.893	0.309	0.707	0.455	0.186***	0.004
Financial independence (index)	0.483	0.237	0.463	0.240	0.021***	0.002
Economic decision (index)	0.768	0.386	0.780	0.377	-0.012***	0.004
Marital harmony (index)	1.056	0.461	1.005	0.458	0.050***	0.005
Domestic violence (index)	0.530	0.334	0.504	0.339	0.026***	0.003
Harassment of girls (dummy)	0.917	0.275	0.893	0.309	0.024***	0.003
Peer group uses mobile phone (number)	3.982	3.419	2.006	2.683	1.976***	0.031
Brahmin caste (dummy)	0.075	0.263	0.032	0.175	0.043***	0.002
General caste (dummy)	0.276	0.447	0.200	0.400	0.076***	0.004
Scheduled caste (dummy)	0.189	0.391	0.232	0.422	-0.043***	0.004
Scheduled tribe (dummy)	0.050	0.218	0.108	0.311	-0.058***	0.003
Other backward caste (dummy)	0.394	0.489	0.414	0.493	-0.020***	0.005
Other caste (dummy)	0.016	0.127	0.014	0.117	0.002**	0.001
Household members (number)	5.266	2.282	5.598	2.591	-0.332***	0.025
Total children (number)	1.546	1.388	1.632	1.551	-0.086***	0.015
Number of sons alive	1.174	0.931	1.440	1.075	-0.266***	0.010
Household assets (index)	18.296	5.912	14.099	6.307	4.197***	0.062
Female head (dummy)	0.082	0.275	0.069	0.253	0.013***	0.003
Education of head (years)	7.102	4.877	4.700	4.521	2.402***	0.047
Age of head (years)	48.628	13.020	48.365	12.147	0.263**	0.127
Owns BPL card (dummy)	0.277	0.448	0.388	0.487	-0.111***	0.005
Urban region (dummy)	0.440	0.496	0.263	0.440	0.176***	0.005
Observations	17,230		22,293		39,523	

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

5.4.2 REGRESSION RESULTS FOR TOTAL SAMPLE

Table 5.4 presents the results of the regression models with women's mobility index as the dependent variable. Column (1) shows the ordinary least squares (OLS) estimates. However, as shown above, women's mobile phone use is endogenous, so that the IV results in column (2) are preferred. The IV estimates suggest that mobile phone use improves women's mobility by 0.084 index points, which is equivalent to a 16% increase relative to the mean mobility index of women not using a mobile phone. This estimate is statistically significant at the 1% level and supports our hypothesis.

Table 5.4: Effects of mobile phones on women's physical mobility

	(1) OLS estimates		(2) IV estimates	
	Coefficient	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)	0.028***	(0.004)	0.084***	(0.019)
Age of respondent (number)	0.018***	(0.001)	0.018***	(0.001)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)
Primary education (dummy)	0.016***	(0.004)	0.008	(0.005)
Secondary education (dummy)	0.024***	(0.005)	0.012*	(0.007)
Higher education (dummy)	0.048***	(0.007)	0.032***	(0.009)
Graduate and above (dummy)	0.068***	(0.008)	0.049***	(0.010)
Mother's education (number)	0.002***	(0.001)	0.002***	(0.001)
Spouse is literate (dummy)	-0.007	(0.004)	-0.008*	(0.004)
Scheduled caste (dummy)	0.004	(0.006)	0.005	(0.006)
Scheduled tribe (dummy)	0.010	(0.009)	0.013	(0.009)
Other backward caste (dummy)	-0.016***	(0.005)	-0.015***	(0.005)
Other caste (dummy)	-0.049***	(0.012)	-0.049***	(0.012)
Household members (number)	-0.003***	(0.001)	-0.001	(0.001)
Total children (number)	0.006***	(0.001)	0.004***	(0.002)
Household assets (index)	0.003***	(0.000)	0.002***	(0.000)
Female head (dummy)	0.059***	(0.021)	0.053**	(0.022)
Education of head (number)	-0.000	(0.000)	-0.000	(0.000)
Age of household head (number)	-0.001***	(0.000)	-0.001***	(0.000)
Owns BPL card (dummy)	-0.014***	(0.004)	-0.015***	(0.004)
Urban region (dummy)	0.026***	(0.006)	0.024***	(0.006)
District fixed effects	Yes		Yes	
Constant	0.172***	(0.025)	0.172***	(0.025)
Observations	34,480		34,480	

Notes: In both models, the mobility index ranging between 0 and 1 is the dependent variable. Standard errors are clustered at the village level. Results with standard errors clustered at the household level are shown in Table D5 in Appendix D. First stage results of the IV model are shown in Table D1 in Appendix D. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

The control variables in Table 5.4 suggest that women's age has a non-linear effect on mobility: with increasing age, mobility first increases but then decreases again for older women. Education increases women's mobility, with higher levels of education having particularly large effects. Furthermore, the mother's education has a positive and significant effect on women's mobility. Somewhat surprisingly, spouse literacy tends to decrease women's physical mobility, even though the effect size is fairly small. In terms of other socioeconomic factors, we find that women from better-off households (higher asset index, no BPL card) are more mobile than women from poorer households.

Table 5.5 presents the results of models with use of contraceptives as the outcome variable (proxy for access to reproductive healthcare services). Column (1) shows marginal effects estimates of a simple probit model. However, as discussed above, accounting for endogeneity is important, so the IV model results in column (2) are more consistent and reliable. The results suggest that mobile phones have a positive and highly significant effect: using a mobile phone increases the likelihood of a woman using contraceptives by 20.2 percentage points. This result supports our hypothesis that mobile phones improve women's access to reproductive healthcare services.

In terms of the control variables in Table 5.5, higher levels of female education seem to reduce the likelihood of using contraceptives, which is a counterintuitive result at first sight. However, this result is largely driven by the widespread use of female sterilization or hysterectomy. Table D.7 in Appendix D shows estimates of models where we differentiate between sterilization/hysterectomy and non-surgical contraceptive methods such as oral pills, copper T, diaphragms, and condoms. The results suggest that women's education decreases the likelihood of female sterilization and hysterectomy, whereas it increases the likelihood of using non-surgical contraceptive methods. These differential effects are plausible in the Indian context. To increase the overall adoption of contraceptive methods, it is probably easier for local health workers to convince women with lower education to undergo female sterilization than women with higher levels of education who may be more aware of alternative methods. Interestingly, and in line with these findings, the results in Table D.7 in Appendix D also suggest that mobile phone use decreases the likelihood of surgical contraception, while it increases the likelihood of using other contraceptive methods.

Table 5.5: Effects of mobile phones on women's use of contraceptives

	(1) Probit estimates		(2) IV estimates	
	Coefficient	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)	0.048***	(0.007)	0.202***	(0.028)
Age of respondent (number)	0.055***	(0.002)	0.063***	(0.002)
Square of age (number)	-0.001***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	0.042***	(0.007)	0.019**	(0.008)
Secondary education (dummy)	0.026***	(0.009)	-0.005	(0.011)
Higher education (dummy)	-0.012	(0.011)	-0.056***	(0.015)
Graduate and above (dummy)	-0.040***	(0.013)	-0.090***	(0.017)
Mother's education (number)	0.000	(0.001)	0.000	(0.001)
Regular or casual work (dummy)	0.061***	(0.007)	0.054***	(0.007)
Scheduled caste (dummy)	0.021**	(0.010)	0.023**	(0.010)
Scheduled tribe (dummy)	0.001	(0.015)	0.008	(0.016)
Other backward caste (dummy)	0.018**	(0.009)	0.022**	(0.009)
Other caste (dummy)	-0.010	(0.023)	-0.012	(0.024)
Household members (number)	0.003**	(0.001)	0.006***	(0.001)
Sons alive (number)	0.064***	(0.003)	0.065***	(0.003)
Household assets (index)	0.005***	(0.001)	0.003***	(0.001)
Female head (dummy)	-0.134***	(0.013)	-0.171***	(0.016)
Education of head (number)	0.001**	(0.001)	0.001	(0.001)
Age of head (number)	-0.001***	(0.000)	-0.001***	(0.000)
Owns BPL card (dummy)	0.000	(0.006)	-0.000	(0.006)
Urban region (dummy)	-0.011	(0.009)	-0.017*	(0.009)
District fixed effects	Yes		Yes	
Constant			-0.795***	(0.056)
Observations	34,923		34,918	

Notes: In both models, the binary outcome "use of contraceptives" is the dependent variable. The estimates shown are marginal effects with standard errors clustered at the village level. Results with standard errors clustered at the household level are shown in Table D.6 in Appendix D. First stage results of the IV model are shown in Table D.1 in Appendix D. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

The other control variables in Table 5.5 suggest that women's off-farm employment and the number of sons alive both increase the likelihood of using contraceptives. Off-farm employment tends to increase women's opportunity costs of staying at home for childcare. The son effect is also plausible in the local context, as in many parts of India the birth of a son is the preferred fertility goal. Once this goal is achieved, the likelihood of using contraceptive methods increases.

As robustness checks, Table 5.6 shows summary results of IV models with additional control variables capturing women's autonomy and women's access to alternative sources of information. The effects of mobile phone use on women's physical mobility and the use of contraceptive methods are very similar to those presented in Table 5.4 and Table 5.5. This adds to the reliability of the findings and suggests that the main estimates are robust to possibly remaining unobserved heterogeneity.

Table 5.6: Robustness checks with additional control variables (summary of IV models)

	Women's autonomy variables additionally included		Access to alternative information sources additionally included	
	Mobility (index)	**Contraceptives (dummy)**	**Mobility (index)**	**Contraceptives (dummy)**
Uses mobile phone (dummy)	0.077***	0.195***	0.085***	0.202***
	(0.017)	(0.028)	(0.019)	(0.029
Control variable included	Yes	Yes	Yes	Yes
Regional fixed effects included	Yes	Yes	Yes	Yes
Observations	34,427	34,867	34,480	34,918

Notes: IV coefficient estimates are shown with standard errors clustered at the village level in parentheses. Full model results are shown in Tables D8 and D9 in Appendix D. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

5.4.3 REGRESSION RESULTS FOR SUBSAMPLES

We now analyse the effects of mobile phones on women's mobility and access to reproductive healthcare services separately for different subsamples, namely women from poor and non-poor households and women from purdah and non-purdah households. The results of these subsample analyses are summarized in Table 5.7. The first important result is that mobile phone use significantly increases women's mobility and the likelihood of using contraceptives for all subsamples. The second important result is that the magnitude of the effects differs between the different groups.

The positive effect of mobile phones on mobility is notably larger for women from poor households than for women from non-poor households. The point estimate of 0.133 for women from poor households (column 1 of Table 5.7) means that their mobility is increased through mobile phones by 26% relative to subsample mean mobility. For comparison, the point estimate of 0.07 for women from non-poor households (column 2) is equivalent to a mobility increase by 14%. Similarly, the positive effect of mobile phones on women's mobility is also somewhat larger in purdah than in non-purdah households (columns 3 and 4). These differences between the subsamples can probably be explained by women in poor and purdah-practicing households being particularly disadvantaged in terms of their access to alternative information and communication channels. In these situations, the positive effects of mobile phones on female mobility are particularly large.

Table 5.7: Effects of mobile phones on different subsamples (summary of IV models)

	Mobility (index)				Use of contraceptives (dummy)			
	By poverty status		By purdah status		By poverty status		By purdah status	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Poor	Non-poor	Purdah	Non-purdah	Poor	Non-poor	Purdah	Non-purdah
Uses mobile phone (dummy)	0.133***	0.077***	0.093***	0.084***	0.209***	0.199***	0.180***	0.229***
	(0.033)	(0.020)	(0.027)	(0.022)	(0.063)	(0.030)	(0.042)	(0.032)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effects included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,945	28,550	20,209	14,282	6,751	32,551	22,972	16,337

Notes: IV coefficient estimates are shown with standard errors clustered at the village level in parentheses. Full model results are shown in Tables D.10-D.13 in Appendix D. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Subsample differences in the magnitude of the mobile phone effects are also observed for the second outcome variable, women's use of contraceptives, but these differences are smaller and partly pointing in the opposite direction (columns 5-8 of Table 5.7). The effect of mobile phones on the likelihood of using contraceptives is very similar for women from poor and non-poor households (20-21 percentage points). For women in non-purdah households the effect is somewhat larger (23 percentage points) than for women in purdah households (18 percentage points). In any case, the results suggest that the use of mobile phones can increase women's access to reproductive healthcare services even in households where traditional social norms and gender segregation play an important role.

5.5 CONCLUSION AND POLICY IMPLICATIONS

Women's economic and social empowerment is facilitated by their ability to move around independently and safely. However, in many developing countries women's mobility is restricted by traditional patriarchal codes of conduct and poor road and transport systems. Restricted female mobility is not only associated with limited access to information but also means lower social participation and worse access to healthcare and related services. Mobile phones could potentially improve the situation for women. Through the use of mobile phones, women can communicate with their social networks and better access information even without leaving the homestead. In addition, mobile phones could help to allay safety concerns when women leave the homestead alone. Finally, better access to information and more frequent communication with family and friends could help to strengthen women's self-confidence and their intra-household bargaining power.

In this article, we used nationally representative data from India to test the hypothesis that women's use of mobile phones increases their physical mobility and their access to reproductive healthcare services. This hypothesis was confirmed. Instrumental variable models with a large set of control variables included suggest that mobile phone use increases women's mobility by 16% and the likelihood of using contraceptive methods by 20 percentage points on average. We also carried out analyses for different subsamples, showing that positive and significant effects are observed for women in all types of households, including poor and non-poor households as well as those practicing and not practicing traditional norms of gender segregation. The positive effects of mobile phones on women's physical mobility are even larger in poor households and households practicing the traditional "purdah" system.

These results suggest that mobile phones can play an important positive role in women's empowerment in traditional societies. This general finding is in line with recent research by Sekabira and Qaim (2017), who showed that mobile phones help to strengthen women's financial autonomy in rural households in Uganda. We are not aware of any previous study that examined the effects of mobile phones on women's physical mobility or their access to reproductive healthcare services, as we have done here.

Our findings have important policy implications. The further spread of mobile phones and related information and communication technologies (ICT) should be promoted in developing countries. This is important for increasing economic efficiency, market functioning, and household incomes, as previous studies showed (e.g., Aker 2010; Beuermann et al. 2012; Parlasca et al. 2020; Torero and von Braun 2006). But it is also important to improve gender equity, as our results here suggest. Of course, the spread of mobile phones alone would not suffice if women had no access to these technologies. Hence, female education and awareness building are important in parallel to further improve mobile technologies, ICT infrastructure, and regulations that are conducive for widespread and affordable access. Mobile phones should be seen as a supplementary mechanism to empower women, not as a substitute for other important policies to improve infrastructure, institutions, and social services for the poor.

In closing, we briefly discuss two limitations of our study, which may also be useful for the design of future research. First, we used cross-section data, because panel data with gendered information on mobile phone use were not available. With cross-section data, identification of causal effects is difficult. While we used an instrumental variable approach to address endogeneity issues and carried out various robustness checks, bias due to unobserved heterogeneity between mobile phone users and non-users cannot be ruled out with certainty. Second, we only looked at two outcome variables, namely women's physical mobility and use of contraceptive methods. To understand the effects of mobile phones on women's empowerment more comprehensively, panel data with suitable outcome variables capturing additional dimensions of gender equity and female wellbeing should be collected and used in follow-up research.

CHAPTER 6: CONCLUSION

6.1 SUMMARY OF THE THESIS

Access to markets is an important determinant for rural households in developing countries to overcome subsistence and enhance their economic situation. However, asymmetric and costly information, often limit market participation or restrict the quantities of goods and labour exchanged. The situation is made worse by infrastructure bottlenecks, less competitive marketing systems, and risky transactions. Under these circumstances, a key policy question for promoting rural development and poverty reduction is: how information constraints faced by rural households can be overcome. One potential mechanism to reduce information constraints is the use of digital technologies, which build on information and communication technologies (ICTs) such as internet platforms and mobile phones. In this context, this dissertation comprises four essays in which it analyses empirically the implications of three types of digital technologies: personalised digital extension services, electronic marketplaces, and mobile phones. This dissertation evaluates the effects of digital technologies on-farm production, markets, off-farm employment, and gender outcomes.

The first essay focuses on an example of a digital technology that reduces information barriers in the input-side of farm production. Using primary observational data from India, this chapter analyses the effects of digital extension services on smallholder agricultural performance. The digital extension services that some of the farmers use provide personalized information on the types of crops to grow, the types and quantities of inputs to use, and other methods of cultivation. Problems of selection bias in the impact evaluation are reduced through propensity score matching combined with estimates of farmers' willingness to pay for digital extension. The results show that the use of personalized digital extension services significantly increases input intensity, production diversity, crop productivity, and levels of commercialization. Total crop income is increased by 25%.

The second essay explores the effects of using a digital tool to connect buyers and sellers in the output market. Using high-frequency cross-sectional time-series data from 2000 to 2017 and applying a fixed-effects approach with Driscoll and Kraay standard errors to deal with spatial and temporal correlation, the second chapter provides empirical evidence on the effects of electronic markets on prices, spikes in prices, and price dispersion of an agro-based commodity—tea— in India. Consistent with search theory, the results suggest that the introduction of electronic markets reduced prices and spikes in tea prices by about 2% between 2000 and 2017. Further electronic marketplaces initially increased price dispersion between markets by about 11-14%, but over time it reduced by 16%.

Subsequently, the third essay analyses the effect of mobile phones on off-farm employment. This chapter argues that the increasing spread of mobile phones could help improve access to employment-related information at relatively low costs. Using nationally representative panel data from rural India and regression models with household fixed effects and an instrumental variable approach this chapter tests the hypothesis that ownership of a mobile phone increases rural households' off-farm employment. The results also suggest that mobile phone ownership significantly increases the likelihood of participating in various types of off-farm employment, including casual wage labour, salaried employment, and non-agricultural self-employment. The effects of mobile phones are significant for all types of rural households but tend to increase with the level of remoteness. The results suggest that mobile phones are effective in improving households' access to off-farm employment, thus contributing to pro-poor rural development and structural transformation.

Finally, the approach of the fourth essay is to think of mobile phones as a tool for improving women's bargaining process, and thus, analyse their effects on gender outcomes. In many developing countries informal institutions (social and gender norms), structural impediments (inadequate and poor quality of roads and transport systems), and security considerations often restrict women's mobility. In this context, where women are physically and economically isolated, mobile phones promise to be an effective instrument to connect them to markets and services by improving access to information, mobilizing interpersonal networks, influencing attitudinal attributes, and improving physical mobility. Using nationally representative data from India collected in 2011-12 and applying an instrumental variable approach, the regression results suggest that mobile phones have a positive and significant effect on women's mobility and access to reproductive healthcare services. Further disaggregation shows that the positive effects are particularly large for women from households below the poverty line. Even women from conservative households and communities, in which veiling and gender seclusion are required, benefit from mobile phones. These findings suggest that mobile phone use among women contributes to female empowerment with positive social welfare implications.

6.2 POLICY IMPLICATIONS

Based on the findings of this dissertation the following points are worth considering from a policy point of view:

1. EQUIPPING PUBLIC EXTENSION AGENTS WITH DIGITAL TECHNOLOGY

Traditionally, the diffusion of agricultural information in developing countries has been promoted through the public extension service, wherein extension agents visit and educate individual farmers or farmer groups. This traditional way of information dissemination has two major drawbacks. First, as personal visits are associated with high transaction costs, only a very limited number of farmers can be reached. Second, the information provided through this channel is often fairly generic and not necessarily well adapted to each farmers' specific needs and conditions. Using digital approaches and technologies can potentially improve the effectiveness of agricultural extension services by reducing transaction costs and improving the quality of the information provided by personalizing the information.

2. INTRODUCING ELECTRONIC MARKETPLACES

Electronic or digital marketplaces have the potential to facilitate access to larger and denser markets, expand trade, improve price discovery through buyer-seller matching and make markets more efficient. The results of this dissertation show that for some non-perishable agriculture products which are storable for a limited period, the introduction of electronic markets can make markets more competitive and efficient. However, 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. The Government of India introduced the electronic National Agriculture Markets (e-NAM) in 2016 intending to digitise all existing agriculture markets. From a policy perspective, the introduction of any digital platform to connect buyers to sellers needs to ensure that:

- There is a system in place that samples, grades, and values the product sold electronically such that buyers from distant regions can build trust and can purchase commodities electronically without seeing the product. Further, sellers can price discriminate depending on the quality of the product. For this, there is a need to invest in grading, sorting, testing, and warehouse infrastructure in agriculture markets.

- There is also a system that enables real-time digital payments such that once an online transaction is completed, producers/sellers receive the money immediately in their bank accounts.

3. INVESTMENT IN DIGITAL INFRASTRUCTURE IN RURAL AREAS

To support innovation and uptake of digital technologies across the agriculture value chain, good quality and accessible mobile and internet networks in rural areas are essential. The type of network infrastructure existing in a region determines the kind of digital application that can be used. For example, voice and text messaging can be used in areas with second-generation network infrastructure, while more sophisticated digital devices and applications can be used in regions where third and fourth-generation networks are available. Thus, to expand network infrastructure in rural areas, the public sector needs to create an enabling environment for the telecom sector and increase competition amongst network providers.

4. INVESTMENT IN COMPLEMENTARY INFRASTRUCTURE

Digital technologies promises to be an important tool to achieve many development outcomes, however, it should not be viewed as a panacea. To achieve the benefits of digital technologies, public sector support in complementary physical infrastructure such as rural electricity, roads, storage, and logistics are required.

5. PROMOTING DIGITAL LITERACY AMONG RURAL HOUSEHOLDS

The adoption of digital technologies in rural areas requires a minimum level of skill to use digital tools such as mobile phones, text messages, applications, and digital platforms. Further, a basic level of literacy is required to critically assess the quality of information and the quality of a digital application. However, in most developing countries low literacy rates— especially amongst marginalised communities and women— may create a digital divide by excluding segments of the rural population from adopting digital technologies. Thus, public-supported capacity building and skill development programs to increase digital literacy can foster an understanding of how to take advantage of digital technologies and stimulate demand for digital technologies.

6.3 CONCLUSION

Emerging digital technologies in agriculture have the potential to change agriculture value chains in developing countries by making it possible to collect, use and analyse large amounts of machine-readable data, and transform business models by significantly reducing the marginal cost of a transaction. The findings of this dissertation suggest that digital technologies can positively affect several developmental outcomes by overcoming transactional costs and information asymmetries. On the farm, improved access to information through personalized digital extension services improves farmers' technical efficiency which translates into better agriculture performance. The thesis further highlights that, off the farm, digital technologies such as electronic marketplaces can reduce search costs and make markets more efficient and reduce spikes in prices. Further, the findings of the dissertation suggests that communication technologies such as mobile phones can improve access to employment-related information at relatively low costs and thereby improve access to labour markets and it can also facilitate institutional changes in the way traditional gender roles are defined by improving women's physical mobility and access to healthcare services.

In closing, few limitations of the dissertation are briefly discussed. In chapter 2, the analysis of the impact of personalised digital extension services on agriculture performance relies on cross-section observational data where the establishment of causality is difficult. Although the essay tries to deal with issues of endogeneity to the extent possible, follow-up research with panel data and/or experimental approaches could be useful to further improve the identification strategy. Further, the results from one example of an agri-tech platform in one region of eastern India should not be generalized. Additional studies in other contexts would be useful to increase the external validity of the results. Chapter 2 concentrates on a few outcome variables related to crop production and income, as this is what the agri-tech platform in the study region focuses on. However, crop productivity and income are not comprehensive measures of household welfare. Future studies could analyse other important outcomes related to food security, time allocation, and gender roles, among others. Moreover, in this chapter effectiveness of the digital platform was measured in terms of improving agricultural performance without considering the costs of providing and using the digital services. Studies on the cost-effectiveness would be useful to gain further policy-relevant insights.

The essays in chapter 3 and chapter 4 uses fixed effect estimation to control for all unobserved time-invariant factors that could be correlated with the decision to transit from physical to the electronic marketplace or use mobile phones respectively. However, it cannot control for unobserved time-varying factors. The essay in chapter 5 also uses cross-section data because panel data with gendered information on mobile phone use were not available. Although the essay uses an instrumental variable approach to address endogeneity issues and carries out various robustness checks, bias due to unobserved heterogeneity between mobile phone users and non-users cannot be ruled out with certainty. Further, in this essay, we only looked at two outcome variables, namely women's physical mobility and use of contraceptive methods. To understand the effects of mobile phones on women's empowerment more comprehensively, panel data with suitable outcome variables capturing additional dimensions of gender equity and female wellbeing should be collected and used in follow-up research.

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APPENDIX A : APPENDIX TO CHAPTER 2

Table: A.1: Number of farmers by village and sample size

		Population			Sample	
Block	**Village**	**FPO vegetable farmers**	**Non-FPO vegetable farmers**	**Non-FPO non-vegetable farmers**	**FPO vegetable farmers**	**Non-FPO vegetable farmers**
Betnoti	Rangada	43 (0.10)	54 (0.05)	24	30	10
	Sribatsapur	52 (0.13)	106 (0.10)	63	37	19
	Demphauda	35 (0.08)	101 (0.10)	57	23	19
	Madhunanda	52 (0.13)	61 (0.06)	10	36	11
	Khadikapada	16 (0.04)	92 (0.09)	144	11	16
	Nakhara	63 (0.15)	114 (0.11)	4	45	20
	Khandadeulia	50 (0.12)	148 (0.14)	12	36	27
	Panchaputuli	22 (0.05)	20 (0.02)	6	15	4
	Raikama	48 (0.12)	193 (0.19)	100	34	35
	Badakhirapada	31 (0.08)	151 (0.15)	8	21	27
Total Betnoti		**412**	**1040**	**428**	**288**	**188**
Badasahi	Bhanjabati	31 (0.07)	63 (0.04)	62	21	11
	Haripur	65 (0.14)	491 (0.28)	255	45	87
	Kuliana	36 (0.08)	121 (0.07)	43	25	21
	Baghuapal	40 (0.09)	61 (0.03)	8	28	11
	Singtia	23 (0.05)	313 (0.18)	150	16	55
	Mankadapal	30 (0.07)	3 (0.002)	8	21	1
	Sakua	64 (0.14)	142 (0.08)	109	44	25
	Chakradharpur	28 (0.07)	157 (0.099	239	19	27
	Khuntapal	55 (0.12)	211 (0.12)	40	38	36
	Sorisakatha	84 (0.18)	221 (0.12)	9	58	40
Total Badasahi		**456**	**1783**	**923**	**315**	**314**

Note: Numbers in parentheses are the proportions relative to the total households in each block.

Table: A.2: Summary statistics of control group farmers by FPO membership

	FPO members		Non-members	
	Mean	**SD**	**Mean**	**SD**
Age of household head (years)	52.72	11.69	49.03	15.12
Male household head (dummy)	0.92	0.27	0.90	0.30
Household head owns a mobile phone (dummy)	0.67	0.47	0.69	0.46
Illiterate (dummy)	0.09	0.29	0.10	0.29
Primary school (dummy)	0.25	0.44	0.28	0.45
Secondary school (dummy)	0.43	0.50	0.39	0.49
Bachelor or Masters (dummy)	0.21	0.41	0.17	0.38
Scheduled tribe (dummy)	0.18	0.39	0.19	0.39
Scheduled caste (dummy)	0.16	0.37	0.22	0.41
Other backward classes (dummy)	0.46	0.50	0.43	0.50
General caste (dummy)	0.20	0.40	0.17	0.38
Household size (number)	3.76	1.43	3.55	1.44
Operated land (acres)	5.09	3.78	3.78	3.90
Irrigation ratio (%)	51.36	34.31	47.22	39.87
Observations	138		502	

[a] Highest education level of adult male. [b] Number of households within the village from the same caste who adopted digital extension services

Table: A.3: : Summary statistics

	Mean	SD	Min	Max
Age of household head (years)	50.50	13.40	21.00	96.00
Male household head (dummy)	0.94	0.24	0.00	1.00
Household head owns a mobile phone (dummy)	0.73	0.44	0.00	1.00
Illiterate [a] (dummy)	0.08	0.27	0.00	1.00
Primary school [a] (dummy)	0.25	0.43	0.00	1.00
Secondary school [a] (dummy)	0.42	0.49	0.00	1.00
Bachelor or Masters [a] (dummy)	0.23	0.42	0.00	1.00
Scheduled tribe (dummy)	0.15	0.35	0.00	1.00
Scheduled caste (dummy)	0.17	0.38	0.00	1.00
Other backward classes (dummy)	0.49	0.50	0.00	1.00
General caste (dummy)	0.19	0.39	0.00	1.00
Household size (number)	3.75	1.43	1.00	11.00
Land ownership (acres)	1.33	1.42	0.00	12.00
Operated land (acres)	4.78	4.03	0.03	36.00
Operational land < 2.5 acres (dummy)	0.32	0.47	0.00	1.00
Operational land 2.5-5 acres (dummy)	0.30	0.46	0.00	1.00
Operational land 5-10 acres (dummy)	0.29	0.45	0.00	1.00
Operational land > 10 acres (dummy)	0.09	0.29	0.00	1.00
Irrigation ratio (%)	50.84	37.47	0.00	116.75
FPO member (dummy)	0.55	0.50	0.00	1.00
Subscriber to digital advisory service (dummy)	0.43	0.50	0.00	1.00
Livestock ownership (livestock units)	1.23	1.18	0.00	21.50
Average distance to input and output market (km)	5.03	4.10	0.00	25.33
Willingness to pay for digital agri-tech platform services	219.84	397.09	10.00	5000.00
Peer group [b]	12.59	9.29	0.00	32.00
Off farm income (dummy)	0.65	0.48	0.00	1.00
Outcome variables				
Number of crops grown	7.25	4.71	1.00	34.00
Seed expenditure (1,000 Rupees/acre)	0.75	0.94	0.00	7.462
Fertilizer expenditure (1,000 Rupees/acre)	1.76	1.51	0.00	13.72
Pesticides expenditure (1,000 Rupees/acre)	0.67	0.86	0.00	10.45
Input expenditure (1,000 Rupees/acre)	3.18	2.91	0.00	31.34
Crop productivity (1,000 Rupees/acre)	15.10	16.28	0.00	221.60
Commercialization (share of farm output sold 0-1)	0.44	0.32	0.00	1.89
Crop income (1,000 Rupees)	35.58	66.52	-116.25	625.51
Observations	1028			

[a] Highest education level of adult male. [b] Number of households within the village from the same caste who adopted digital extension services

Table: A.4 : OLS estimates with WTP as additional control variable (robustness check)

	(1) Number of crops	(2) Seed expenditure (log)	(3) Fertilizer expenditure (log)	(4) Pesticide expenditure (log)	(5) Input expenditure (log)	(6) Crop productivity (log)	(7) Crop commercialization (0-1)	(8) Crop income (log)
Digital extension (dummy)	0.934***	0.206***	0.164***	0.190***	0.189***	0.170***	0.052***	0.200**
	(0.295)	(0.073)	(0.050)	(0.064)	(0.051)	(0.053)	(0.019)	(0.091)
WTP and other controls included [a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1028	933	1005	938	1018	1024	1024	860
R-squared	0.295	0.354	0.322	0.389	0.363	0.202	0.305	0.395

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. Robust standard errors are shown in parentheses. [a] Controls included are the same as in Table 3.

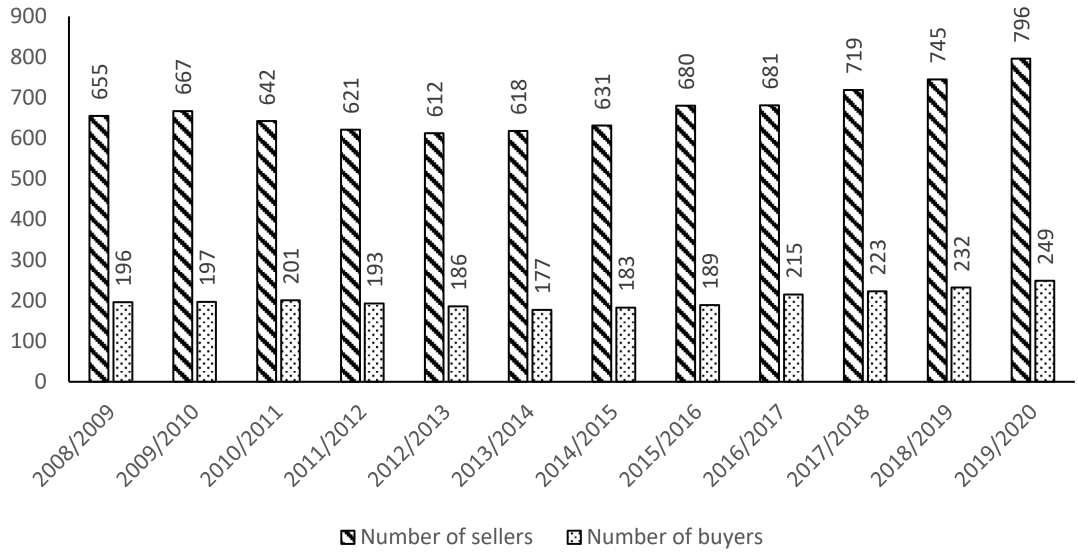
Table: A.5: PSM estimates excluding potentially endogenous variables (robustness check)

	Nearest neighbour matching		Radius matching		Kernel matching	
Outcome variable	**ATT**	**SE**	**ATT**	**SE**	**ATT**	**SE**
Number of crops grown	1.061**	(0.422)	1.072***	(0.345)	1.120***	(0.350)
Seed expenditure per acre (log)	0.253**	(0.116)	0.240**	(0.098)	0.230**	(0.092)
Fertilizer expenditure per acre (log)	0.164**	(0.079)	0.168***	(0.061)	0.161**	(0.063)
Pesticide expenditure per acre (log)	0.239**	(0.098)	0.235***	(0.081)	0.223***	(0.082)
Total expenditure per acre (log)	0.221***	(0.076)	0.219**	(0.064)	0.211***	(0.064)
Crop productivity (log)	0.185***	(0.071)	0.189***	(0.058)	0.182***	(0.058)
Crop commercialization	0.050*	(0.027)	0.049**	(0.023)	0.051**	(0.023)
Crop income (log)	0.244*	(0.126)	0.261**	(0.102)	0.273**	(0.109)

Note: Ownership of mobile phones, off-farm income, and peer group were the three potentially endogenous variables excluded in these calculations. ATT: Average treatment effect on the treated. Bootstrapped standard errors with 1000 replications are shown in parentheses. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level

APPENDIX B : APPENDIX TO CHAPTER 3

Figure: B.1 Number of buyers and sellers in Guwahati tea auction center



Source: Own presentation based on data from Guwahati tea auction center

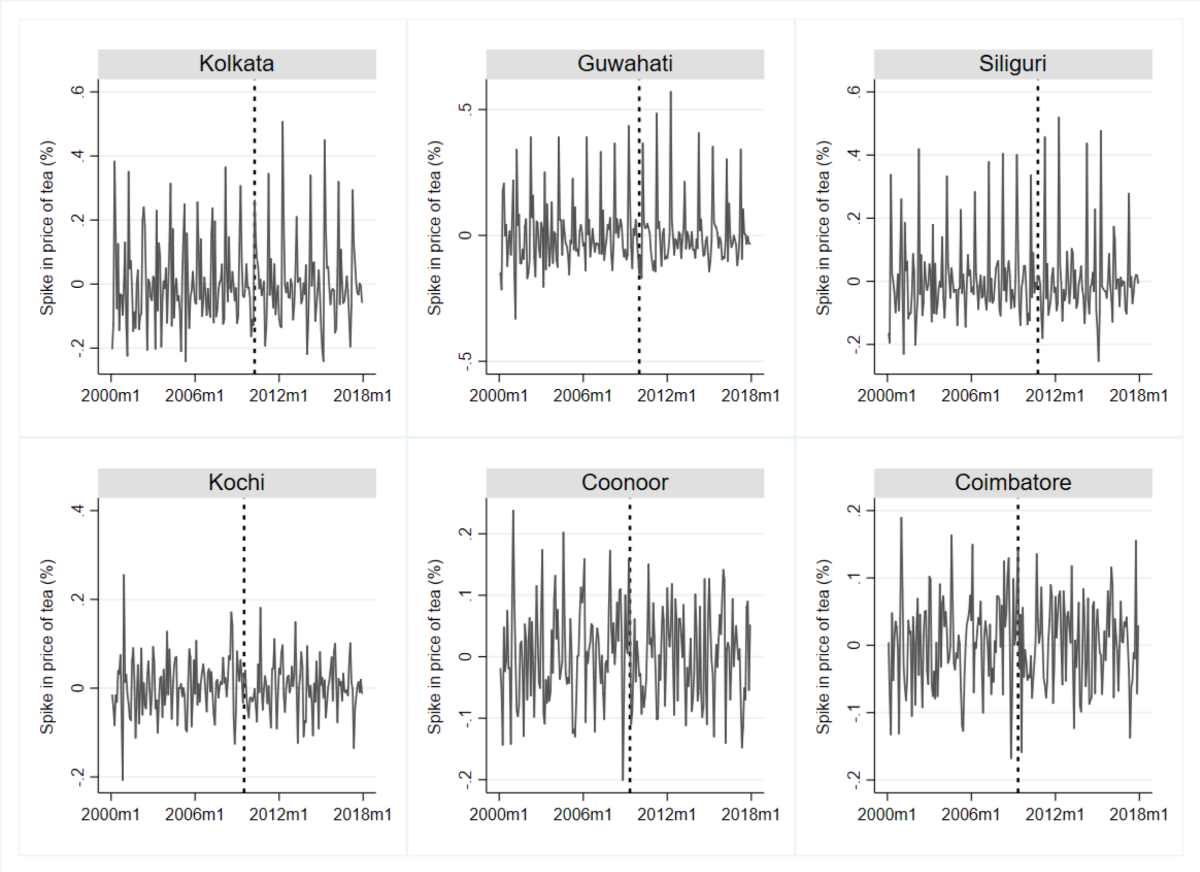
Table: B.1: Results of augmented Dickey-Fuller and Phillips–Perron unit root test

	Augmented Dickey–Fuller		**Phillips–Perron**	
	Test statistics (Z)	**p-value**	**Test statistics (Z)**	**p-value**
Real auction prices (log)	-15.750	0.000	-13.640	0.000
Spike in auction price (%)	-19.859	0.000	-19.904	0.000
Auction arrivals (log)	-15.206	0.000	-17.379	0.000
World tea price index (log)	-3.727	0.000	-2.651	0.004
Spike in diesel price (log)	-19.904	0.000	-19.904	0.000
Rainfall (log)	-16.847	0.000	-19.571	0.000
Lagged rainfall (t-1) (log)	-16.860	0.000	-19.527	0.000
Lagged auction prices (t-1) (log)	-15.693	0.000	-13.582	0.000

The null hypothesis is that all the panels contain a unit root

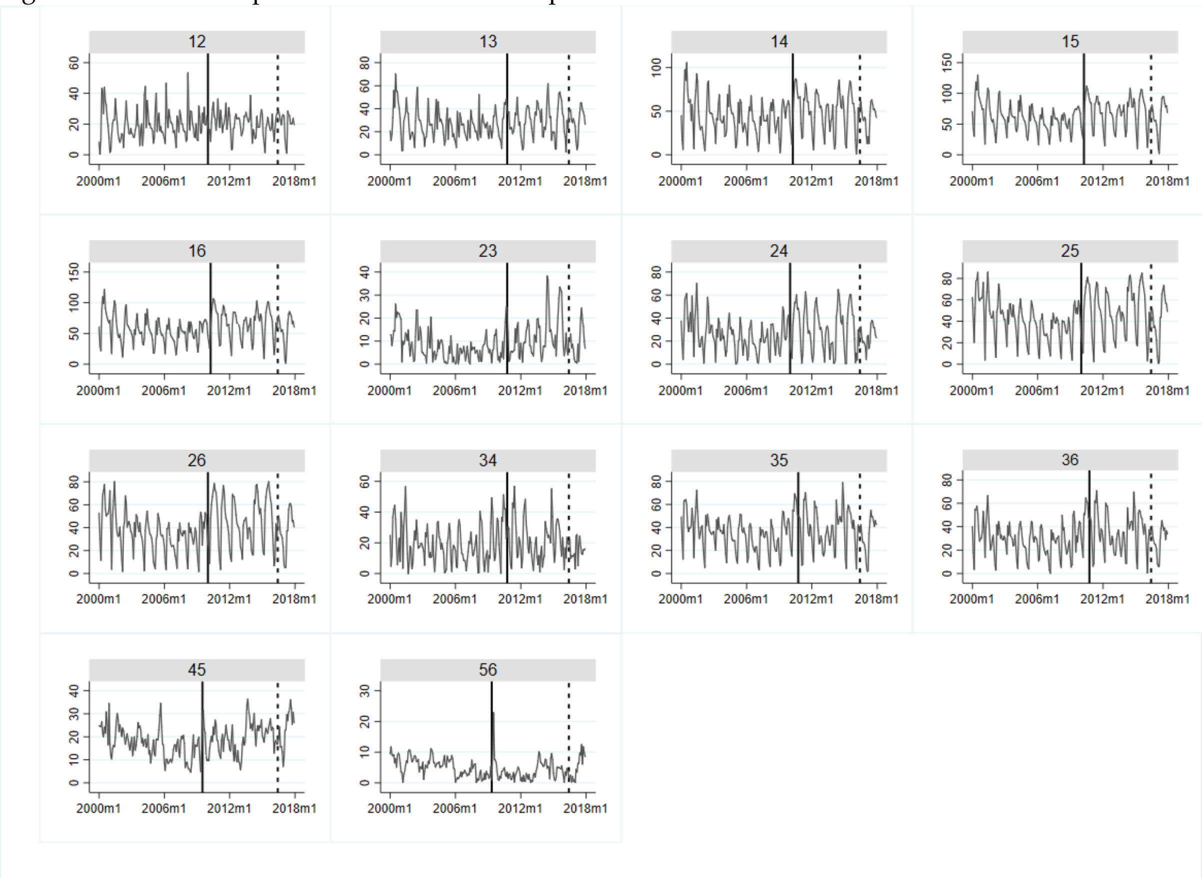
All series include a time trend with 1 lag and cross-sectional means have been subtracted from all series except world tea price index.

Figure: B.2: Spike in tea prices in different markets in India



Auction prices have been deflated by the wholesale price index at 2012 prices. Spike in auction prices is measured as log(P_t)-log(P_{t-1}), where P_t is the real price of tea at time t. Coonoor and Coimbatore introduced electronic marketplace in May 2009, Cochin in July 2009, Guwahati in January 2010, Kolkata in April 2010, and Siliguri in October 2010

Figure: B.3: Absolute price difference between pairs of auction centers in India



Codes for auction centres: 1-Kolkata, 2-Guwahati, 3-Siliguri, 4-Kochi, 5-Coonoor and 6-Coimbatore. Coonoor and Coimbatore introduced electronic marketplace in May 2009, Cochin in July 2009, Guwahati in January 2010, Kolkata in April 2010, and Siliguri in October 2010.

Solid vertical line depicts the month when both auction centres had electronic marketplace and dotted vertical line depicts the month when all India trading was allowed i.e., June 2016.

Table: B.2: Effects of electronic marketplace on price levels

	Dependent variable [$log(P_{i,t})$]						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Electronic auction (dummy)	0.038**	-0.044***	-0.028***	-0.028*	-0.028***	-0.028*	-0.022*
	(0.015)	(0.016)	(0.009)	(0.014)	(0.006)	(0.015)	(0.012)
World tea price index (log)		0.211***	0.082***	0.082***	0.082***	0.082***	0.067***
		(0.027)	(0.016)	(0.024)	(0.007)	(0.026)	(0.022)
Rainfall (log)		-0.007	-0.000	-0.000	-0.000	-0.000	-0.001
		(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Lagged rainfall (t-1) (log)		0.004	0.007**	0.007	0.007*	0.007	-0.004
		(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)
Spike in diesel price		0.312**	0.166	0.166	0.166**	0.166	0.169
		(0.139)	(0.107)	(0.190)	(0.046)	(0.190)	(0.178)
Lagged auction prices (t-1) (log)			0.788***	0.788***	0.788***	0.788***	0.840***
			(0.019)	(0.027)	(0.025)	(0.024)	(0.021)
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 x monthly time dummy	No	No	No	No	No	No	Yes
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared ††	0.005	0.721	0.902	0.902	0.902	0.700	0.826

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. $P_{i,t}$ is the auction prices of tea in period t in auction centre *i*. Robust standard errors in parentheses (column 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 centres to correct for spatial dependence. In column (6) and column (7) 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 wholesale price index at 2012 prices. † World tea price index created by taking average auction prices in Mombasa and Colombo auction and deflating prices by 2012 prices. †† Column (6) and (7) presents within R-squared

Table: B.3: Effects of electronic marketplace on prices dispersion

	(1)	(2)
	Dependent variable [$\log\lvert P_{jt} - P_{kt}\rvert$]	
Both markets have electronic marketplace (dummy)	0.132*	0.109
	(0.068)	(0.068)
Pan India electronic trading (dummy)		-0.273***
		(0.096)
World tea price index † (log)	0.212*	0.224*
	(0.126)	(0.124)
Absolute arrivals dispersion between markets (log)	-0.004	-0.009
	(0.016)	(0.015)
Average rainfall in tea growing regions (log)	-0.002	-0.013
	(0.022)	(0.022)
Spike in diesel price	0.255	0.339
	(0.511)	(0.515)
Lagged absolute price dispersion (t-1) (log)	0.365***	0.380***
	(0.043)	(0.041)
Monthly time dummy	Yes	Yes
Common time trend	Yes	Yes
Group-specific time trend	Yes	Yes
Market fixed effect	Yes	Yes
Both markets in the same region x monthly time dummy	Yes	Yes
Observations	29,33	3,217
within R-squared	0.516	0.517

* Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. Driscoll and Kraay standard errors are presented in parentheses to correct for heteroscedasticity, autocorrelation and contemporary correlation.

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

Table: B.4: Effects of electronic marketplace on prices dispersion

	Dependent variable [$\log\lvert P_{jt} - P_{kt}\rvert$]								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Both auction centres have e-auction (dummy)	0.141**	0.201***	0.138***	0.138***	0.138***	0.138***	0.138**	0.114*	0.108
	(0.054)	(0.049)	(0.046)	(0.046)	(0.053)	(0.020)	(0.068)	(0.068)	(0.068)
Pan India electronic trading (dummy)								-0.274***	-0.274***
								(0.098)	(0.097)
World tea price index † (log)		0.361***	0.209***	0.209***	0.209**	0.209	0.209*	0.221*	0.223*
		(0.087)	(0.080)	(0.080)	(0.103)	(0.120)	(0.126)	(0.124)	(0.124)
Average rainfall in tea growing regions (log)		-0.001	0.001	0.001	0.001	0.001	0.001	-0.011	-0.013
		(0.021)	(0.020)	(0.020)	(0.021)	(0.019)	(0.022)	(0.023)	(0.022)
Spike in diesel price		0.383	0.255	0.255	0.255	0.255	0.255	0.343	0.345
		(0.370)	(0.361)	(0.361)	(0.531)	(0.288)	(0.517)	(0.522)	(0.521)
Lagged absolute price dispersion (t-1) (log)			0.362***	0.362***	0.362***	0.362***	0.362***	0.377***	0.379***
			(0.032)	(0.032)	(0.041)	(0.031)	(0.041)	(0.039)	(0.041)
Monthly time dummy		No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common time trend		No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend		No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market fixed effect		No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Both markets in the same region x monthly time dummy		No	No	No	No	No	No	No	Yes
Observations	2,954	2,934	2,933	2,933	2,933	2,933	2,933	3,217	3,217
R-squared ᒥᒥ	0.497	0.668	0.719	0.719	0.719	0.719	0.445	0.453	0.516

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

In Column (1-7), regressions are conducted for the period Jan 2000 to May 2016.

Robust standard errors in parentheses (Column 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 centres to correct for spatial dependence. In Column (6) and Column (7), Driscoll and Kraay standard errors are presented in parentheses to correct for heteroscedasticity, autocorrelation and contemporary correlation.

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

ᒥᒥ Column (7), (8) and (9) presents within R-squared

APPENDIX C : APPENDIX TO CHAPTER 4

Table: C.1: First stage regression results (FE-LPM model)

	Coefficient	**SE**
Adoption of mobile phones at village level (proportion)	0.711***	(0.019)
Male household head (dummy)	0.043***	(0.009)
Age of household head (years)	-0.002***	(0.000)
Education of household head (years)	0.013***	(0.001)
Household size (number)	0.005***	(0.001)
Household owns BPL ration card (dummy)	0.027***	(0.006)
Household owns APL ration card (dummy)	0.030***	(0.006)
Credit in last five years (dummy)	0.032***	(0.004)
Household assets (index)	0.023***	(0.001)
Membership in social groups (index)	0.002	(0.002)
Cultivated land <2.5 acres (dummy)	-0.018***	(0.007)
Cultivated land 2.5-5 acres (dummy)	-0.003	(0.008)
Cultivated land 5-10 acres (dummy)	-0.003	(0.007)
Number of livestock (livestock units)	-0.005*	(0.003)
Year 2012 (dummy)	0.206***	(0.013)
R-squared	0.750	
F-statistic	1,459.47***	
Kleibergen-Paap Lagrange multiplier statistic	166.28***	
Observations	54,530	

Notes: The dependent variable is a dummy variable of mobile phone ownership. BPL, below the poverty line. APL, above the poverty line.

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

Table: C.2: Association between instrument and outcome variables

Outcome variables	**Instrument (village-level mobile phone adoption)**	
	Correlation coefficient	***p*-value**
Off-farm employment	0.004	0.324
Casual wage employment	-0.004	0.332
Salaried employment	0.044	0.000
Self-employment	-0.001	0.861

Table: C.3: Association between instrument and salaried employment (FE-LPM)

	Coefficient	**SE**
Adoption of mobile phones at village level (proportion)	-0.007	(0.015)
Household owns mobile phone (dummy)	0.032***	(0.007)
Male household head (dummy)	0.042***	(0.010)
Age of household head (years)	-0.000	(0.000)
Education of household head (years)	0.011***	(0.001)
Household size (number)	0.007***	(0.001)
Household owns BPL ration card (dummy)	-0.007	(0.005)
Credit in last five years (dummy)	0.013***	(0.005)
Household assets (index)	0.004***	(0.001)
Social group membership (index)	0.008***	(0.002)
Cultivated land <2.5 acres (dummy)	0.021***	(0.007)
Cultivated land 2.5-5 acres (dummy)	0.007	(0.008)
Cultivated land 5-10 acres (dummy)	0.009	(0.008)
Number of livestock (livestock units)	-0.005*	(0.003)
Distance to district capital (km)	-0.000	(0.000)
Year 2012 (dummy)	-0.020*	(0.010)
Peer group (employment network, salaried)	0.034***	(0.002)
Constant	-0.083***	(0.020)
Observations	53,160	
F-statistic	51.92***	

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

Table: C.4: Descriptive statistics by mobile phone ownership (2005)

	With mobile phone		**Without mobile phone**			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**SE**
Male household head (dummy)	0.896	0.305	0.912	0.283	-0.0162	0.010
Age of household head (years)	53.393	13.446	48.201	13.441	5.191***	0.472
Education of household head (years)	11.706	3.387	6.279	4.836	5.428***	0.168
Household size (number)	7.377	4.033	5.993	3.135	1.384***	0.111
Household has BPL ration card (dummy)	0.154	0.361	0.380	0.485	-0.226***	0.017
Household has APL ration card (dummy)	0.763	0.426	0.456	0.498	0.306***	0.017
Credit in last five years (dummy)	0.426	0.495	0.475	0.499	-0.0490***	0.018
Household assets (index)	14.206	3.434	7.856	3.401	6.350***	0.119
Cultivated land <2.5 acres (dummy)	0.442	0.497	0.610	0.488	-0.169***	0.017
Cultivated land 2.5-5 acres (dummy)	0.093	0.291	0.111	0.314	-0.0178	0.011
Cultivated land 5-10 acres (dummy)	0.161	0.368	0.115	0.319	0.0460***	0.011
Cultivated land >10 acres (dummy)	0.261	0.440	0.135	0.342	0.126***	0.012
Number of livestock (livestock units)	1.204	1.766	0.838	1.263	0.366***	0.045
Distance to tarmac road (km)	0.638	2.276	1.658	4.221	-1.020***	0.149
Distance to closest bus stop (km)	1.391	3.062	1.983	3.394	-0.591***	0.120
Distance to district capital (km)	34.321	24.113	45.018	26.951	-10.70***	0.956
Social group membership (index)	1.526	1.652	1.172	1.398	0.354***	0.049
Employment network (all off-farm)	8.119	8.427	9.386	7.991	-1.267***	0.281
Employment network (casual wage)	4.216	6.014	6.770	6.471	-2.554***	0.227
Employment network (salaried)	3.192	3.411	2.309	3.240	0.883***	0.114
Employment network (self-employed)	2.092	2.797	1.903	2.750	0.188*	0.097
Adoption of mobile phones at village level	0.105	0.102	0.027	0.055	0.0782***	0.002
Off-farm employment (dummy)	0.724	0.447	0.794	0.405	-0.0695***	0.014
Casual wage employment (dummy)	0.142	0.349	0.578	0.494	-0.436***	0.017
Salaried employment (dummy)	0.428	0.495	0.190	0.393	0.238***	0.014
Self-employment (dummy)	0.326	0.469	0.162	0.368	0.164***	0.013
Observations	838		26,434		27,272	

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

Table: C.5: Descriptive statistics by year

	2005		2012			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**SE**
Household owns mobile phone (dummy)	0.031	0.173	0.744	0.436	0.713***	0.003
Male household head (dummy)	0.912	0.284	0.858	0.349	-.0540***	0.003
Age of household head (years)	48.361	13.471	49.518	13.932	1.158***	0.117
Education of household head (years)	6.445	4.888	7.134	4.915	0.689***	0.042
Household size (number)	6.035	3.176	4.899	2.382	-1.136***	0.024
Household has BPL ration card (dummy)	0.373	0.484	0.389	0.488	0.0156***	0.004
Household has APL ration card (dummy)	0.466	0.499	0.428	0.495	-0.0377***	0.004
Credit in last five years (dummy)	0.474	0.499	0.584	0.493	0.111***	0.004
Household assets (index)	8.051	3.574	8.970	3.580	0.918***	0.031
Cultivated land <2.5 acres (dummy)	0.605	0.489	0.543	0.498	-0.0620***	0.004
Cultivated land 2.5-5 acres (dummy)	0.110	0.313	0.096	0.295	-0.0140***	0.003
Cultivated land 5-10 acres (dummy)	0.116	0.321	0.111	0.314	-0.00590**	0.003
Cultivated land >10 acres (dummy)	0.139	0.346	0.226	0.418	0.0871***	0.003
Number of livestock (livestock units)	0.849	1.283	0.603	0.890	-0.246***	0.009
Distance to tarmac road (km)	1.627	4.179	0.614	2.839	-1.012***	0.031
Distance to closest bus stop (km)	1.965	3.386	2.071	3.979	0.106***	0.032
Distance to district capital (km)	44.694	26.931	45.127	31.778	0.433*	0.255
Social group membership (index)	1.183	1.408	1.417	1.424	0.234***	0.012
Employment network (all off-farm)	9.347	8.007	9.587	8.014	0.240***	0.069
Employment network (casual wage)	6.691	6.472	7.266	6.710	0.575***	0.056
Employment network (salaried)	2.336	3.249	2.292	2.692	-0.0444*	0.026
Employment network (self-employed)	1.909	2.752	1.809	2.622	-0.0999***	0.023
Adoption of mobile phones at village level	0.029	0.059	0.706	0.185	0.677***	0.001
Off-farm employment (dummy)	0.792	0.406	0.806	0.395	0.0147***	0.003
Casual wage employment(dummy)	0.565	0.496	0.610	0.488	0.0454***	0.004
Salaried employment (dummy)	0.198	0.398	0.199	0.400	0.00172	0.003
Self-employment (dummy)	0.167	0.373	0.154	0.361	-0.0127***	0.003
Observations	27,272		27,272		54,544	

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

Table: C.6: Effects of mobile phone ownership on off-farm employment (IV-FE-LPM models)

	(1) Off-farm employment		(2) Casual wage employment		(3) Salaried employment		(4) Self-employment	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Mobile phone (dummy) [a]	0.075**	(0.037)	0.069*	(0.041)	0.055*	(0.031)	0.187***	(0.038)
Male head (dummy)	0.131***	(0.010)	0.080***	(0.011)	0.036***	(0.010)	0.032***	(0.009)
Age of head (years)	-0.002***	(0.000)	-0.001***	(0.000)	-0.000	(0.000)	0.001**	(0.000)
Education of head (years)	0.007***	(0.001)	0.000	(0.001)	0.011***	(0.001)	-0.001	(0.001)
Household size (number)	0.015***	(0.001)	0.015***	(0.002)	0.008***	(0.001)	0.005***	(0.001)
BPL ration card (dummy)	0.009	(0.006)	0.028***	(0.008)	-0.015**	(0.007)	-0.000	(0.007)
APL ration card (dummy)	-0.004	(0.007)	-0.008	(0.009)	-0.007	(0.007)	0.006	(0.007)
Credit (dummy)	0.030***	(0.005)	0.033***	(0.006)	0.014***	(0.005)	0.020***	(0.005)
Household assets (index)	-0.008***	(0.002)	-0.020***	(0.002)	0.004***	(0.001)	0.007***	(0.001)
Social group membership	0.009***	(0.002)	0.003	(0.002)	0.006***	(0.002)	0.008***	(0.002)
Land <2.5 acres (dummy)	0.062***	(0.009)	0.050***	(0.010)	0.019**	(0.008)	0.009	(0.008)
Land 2.5-5 acres (dummy)	-0.006	(0.011)	-0.002	(0.012)	0.006	(0.009)	-0.002	(0.009)
Land 5-10 acres (dummy)	-0.014	(0.011)	-0.012	(0.011)	0.007	(0.008)	-0.016*	(0.009)
Number of livestock (units)	-0.023***	(0.003)	-0.019***	(0.003)	-0.006**	(0.003)	-0.009***	(0.003)
Year 2012 (dummy)	-0.018	(0.026)	0.030	(0.028)	-0.040*	(0.021)	-0.150***	(0.027)
Constant	0.642***	(0.025)	0.570***	(0.025)	0.006	(0.022)	0.007	(0.020)
Observations	54,537		54,537		54,537		54,537	

Notes: Standard errors are robust and clustered at village level. Mobile phone ownership is instrumented with adoption rate of mobile phones at village level (excluding the specific household). First-stage regression models are shown in Table C.1.
* Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.

Table: C.7: Effects of mobile phones on different types of off-farm employment by distance to district capital (FE-LPM models)

	Casual wage employment (dummy)		**Salaried wage employment (dummy)**		**Self-employment (dummy)**	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Mobile phone (MP, dummy)	0.0247***	(0.0089)	0.0414***	(0.0086)	0.0366***	(0.0075)
Distance to district capital (km)	-0.0000	(0.0002)	0.0001	(0.0001)	0.0000	(0.0002)
MP x Distance to district capital	0.0004***	(0.0001)	-0.0002*	(0.0001)	-0.0003***	(0.0001)
Male household head (dummy)	0.0785***	(0.0104)	0.0423***	(0.0097)	0.0394***	(0.0079)
Age of household head (years)	-0.0012***	(0.0003)	-0.0001	(0.0002)	0.0003	(0.0002)
Education of head (years)	0.0000	(0.0008)	0.0109***	(0.0008)	0.0021***	(0.0006)
Household size (number)	0.0154***	(0.0015)	0.0073***	(0.0013)	0.0061***	(0.0012)
BPL ration card (dummy)	0.0262***	(0.0068)	-0.0107*	(0.0064)	0.0044	(0.0057)
APL ration card (dummy)	-0.0024	(0.0076)	-0.0065	(0.0064)	0.0114*	(0.0060)
Credit (dummy)	0.0303***	(0.0050)	0.0127***	(0.0048)	0.0212***	(0.0045)
Household assets (index)	-0.0186***	(0.0014)	0.0042***	(0.0012)	0.0110***	(0.0011)
Social group membership	0.0029	(0.0020)	0.0080***	(0.0018)	0.0062***	(0.0017)
Land <2.5 acres (dummy)	0.0447***	(0.0085)	0.0207***	(0.0073)	0.0079	(0.0071)
Land 2.5-5 acres (dummy)	-0.0033	(0.0101)	0.0072	(0.0084)	-0.0024	(0.0082)
Land 5-10 acres (dummy)	-0.0094	(0.0097)	0.0090	(0.0079)	-0.0134*	(0.0076)
Number of livestock (units)	-0.0168***	(0.0032)	-0.0047*	(0.0026)	-0.0098***	(0.0028)
Employment network	0.0392***	(0.0016)	0.0344***	(0.0020)	0.0404***	(0.0020)
Year 2012 (dummy)	0.0271***	(0.0057)	-0.0241***	(0.0053)	-0.0311***	(0.0053)
Constant	0.3046***	(0.0243)	-0.0880***	(0.0207)	-0.1193***	(0.0183)
Observations	53,160		53,160		53,160	
F-statistic	76.52***		51.40***		55.34***	
Hausman test, chi-squared	2485.78***		6805.08***		11703.77***	

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

APPENDIX D : APPENDIX TO CHAPTER 5

Table: D.1: First stage regression results of IV models (women's mobile phone use)

	(1) Mobility model		(2) Use of contraceptives model	
	Coefficient	**SE**	**Coefficient**	**SE**
Peer group using mobile phone (number)	0.043***	(0.002)	0.040***	(0.002)
Age of respondent (number)	0.019***	(0.002)	0.020***	(0.002)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)
Primary education (dummy)	0.135***	(0.008)	0.138***	(0.007)
Secondary education (dummy)	0.198***	(0.010)	0.203***	(0.010)
Higher education (dummy)	0.279***	(0.013)	0.276***	(0.012)
Graduate and above (dummy)	0.328***	(0.014)	0.322***	(0.013)
Mother's education (number)	0.002**	(0.001)	0.002*	(0.001)
Spouse is literate (dummy)	0.025***	(0.008)	0.036***	(0.006)
Scheduled caste (dummy)	-0.015	(0.009)	-0.026***	(0.009)
Scheduled tribe (dummy)	-0.015	(0.013)	-0.028**	(0.013)
Other backward caste (dummy)	-0.015*	(0.008)	-0.017**	(0.008)
Other caste (dummy)	0.010	(0.026)	0.003	(0.025)
Household members (number)	-0.030***	(0.002)	-0.015***	(0.001)
Total children (number)	0.038***	(0.003)	0.008***	(0.003)
Household assets (index)	0.014***	(0.001)	0.014***	(0.001)
Female head (dummy)	0.123***	(0.046)	0.119***	(0.009)
Education of head (number)	0.002***	(0.001)	0.003***	(0.001)
Age of household head (number)	0.001**	(0.000)	0.001**	(0.000)
Owns BPL card (dummy)	0.015**	(0.006)	0.008	(0.006)
Urban region (dummy)	0.049***	(0.011)	0.044***	(0.010)
District fixed effects	Yes		Yes	
Constant	-0.408***	(0.042)	-0.391***	(0.040)
Observations	34,480		39,309	
Model F-statistic	454.035***		583.101***	
Test of exogeneity of mobile phone use				
Durbin χ^2 statistic	37.447***		71.014***	
Wu-Hausman F-statistic	37.397***		70.989***	

Notes: Standard errors are clustered at the village level. * Significant at 10% level; ** Significant at 5% level; ***Significant at 1% level.

Table: D.2: Correlation between instrument and outcome variables

Outcome variable	Peer group using mobile phone (number)	
	Correlation coefficient	*p*-value
Mobility		
Mobility index	-0.0001	0.9875
Access to reproductive healthcare services		
Use of contraceptives (dummy)	-0.0079	0.1365

Table: D.3: Measuring women's autonomy

Variables included in creating indexes
1. Financial independence index
• Respondent participates in regular or casual work (dummy)
• Respondent's name is on the bank account (dummy)
• Respondent has cash in hand for household expenditure (dummy)
2. Agency in decision making index
• Respondent decides to buy land or property (dummy)
• Respondent decides to purchase expensive items (dummy)
• Respondent decides on wedding expenses (dummy)
• Respondent decides what to cook daily (dummy)
• Respondent decides on how many children to have (dummy)
• Respondent decides what to do if she falls sick (dummy)
• Respondent decides what to do if the child falls sick (dummy)
• Respondent decides to whom her children should marry (dummy)
• Respondent does food shopping (dummy)
3.Percecption about women's safety
a. Perceptions about domestic violence (index)
Unusual in the community for the husband to beat:
• If she leaves home without permission (dummy)
• If he suspects extramarital affair (dummy)
• If natal family does not live up to expectations (dummy)
• If she neglects house or child (dummy)
• If she disrespects elders (dummy)
• If she does not cook properly (dummy)
b. Perceptions about harassment of unmarried women in the community
• Whether harassment of unmarried girls is rare in the neighbourhood (dummy)
4. Marital harmony index
• Respondent discusses with husband about work or farm (0=never; 1=sometimes; 2=often)
• Respondent discusses with husband about expenditures (0=never; 1=sometimes; 2=often)
• Respondent discusses with husband about community or politics (0=never; 1=sometimes; 2=often)
• Respondent eats together with family (0=never; 1=sometimes; 2=often)

Note: Indexes for the different categories are calculated by taking the unweighted mean of the different variables in each category.

Table: D.4: Measuring women's access to alternative sources of information

Variables included
Women in the house listen to the radio sometimes or regularly (dummy)
Women in the house watch television sometimes or regularly (dummy)
Women in the house read the newspaper sometimes or regularly (dummy)

Table: D.5: Effect of mobile phones on mobility (standard errors clustered at the household level)

	(1)		(2)	
	OLS estimates		**IV estimates**	
	Coefficient	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)	0.028***	(0.003)	0.084***	(0.010)
Age of respondent (number)	0.018***	(0.001)	0.018***	(0.001)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)
Primary education (dummy)	0.016***	(0.003)	0.008**	(0.004)
Secondary education (dummy)	0.024***	(0.004)	0.012**	(0.005)
Higher education (dummy)	0.048***	(0.006)	0.032***	(0.007)
Graduate and above (dummy)	0.068***	(0.007)	0.049***	(0.008)
Mother's education (number)	0.002***	(0.000)	0.002***	(0.000)
Spouse is literate (dummy)	-0.007*	(0.004)	-0.008**	(0.004)
Scheduled caste (dummy)	0.004	(0.004)	0.005	(0.004)
Scheduled tribe (dummy)	0.010**	(0.005)	0.013**	(0.005)
Other backward caste (dummy)	-0.016***	(0.003)	-0.015***	(0.003)
Other caste (dummy)	-0.049***	(0.010)	-0.049***	(0.010)
Household members (number)	-0.003***	(0.001)	-0.001	(0.001)
Total Children (number)	0.006***	(0.001)	0.004***	(0.001)
Household assets (index)	0.003***	(0.000)	0.002***	(0.000)
Female head (dummy)	0.059***	(0.020)	0.053***	(0.020)
Education of head (number)	-0.000	(0.000)	-0.000	(0.000)
Age of head (number)	-0.001***	(0.000)	-0.001***	(0.000)
Owns BPL card (dummy)	-0.014***	(0.003)	-0.015***	(0.003)
Urban region (dummy)	0.026***	(0.003)	0.024***	(0.003)
District fixed effects	Yes		Yes	
Constant	0.172***	(0.019)	0.172***	(0.019)
Observations	34,480		34,480	

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

Table: D.6: Effect of mobile phones on women's use of contraceptives (standard errors clustered at the household level)

	(1) Probit estimates		(2) IV estimates	
	Coefficient	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)	0.048***	(0.005)	0.202***	(0.019)
Age of respondent (number)	0.055***	(0.002)	0.063***	(0.002)
Square of age (number)	-0.001***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	0.042***	(0.006)	0.019***	(0.007)
Secondary education (dummy)	0.026***	(0.008)	-0.005	(0.009)
Higher education (dummy)	-0.012	(0.011)	-0.056***	(0.013)
Graduate and above (dummy)	-0.040***	(0.012)	-0.090***	(0.015)
Mother's education (number)	0.000	(0.001)	0.000	(0.001)
Regular or casual work (dummy)	0.061***	(0.006)	0.054***	(0.006)
Scheduled caste (dummy)	0.021***	(0.007)	0.023***	(0.007)
Scheduled tribe (dummy)	0.001	(0.009)	0.008	(0.010)
Other backward caste (dummy)	0.018***	(0.006)	0.022***	(0.006)
Other caste (dummy)	-0.010	(0.019)	-0.012	(0.020)
Household member (number)	0.003**	(0.001)	0.006***	(0.001)
Sons alive (number)	0.064***	(0.003)	0.065***	(0.003)
Household assets (index)	0.005***	(0.001)	0.003***	(0.001)
Female head (dummy)	-0.134***	(0.012)	-0.171***	(0.014)
Education of head (number)	0.001**	(0.001)	0.001	(0.001)
Age of head (number)	-0.001***	(0.000)	-0.001***	(0.000)
Owns BPL card (dummy)	0.000	(0.005)	-0.000	(0.005)
Urban region (dummy)	-0.011*	(0.006)	-0.017***	(0.006)
District fixed effects	Yes		Yes	
Constant			-0.795***	(0.041)
Observations	34,923		34,918	

Notes: In both models, the binary outcome use of contraceptives is the dependent variable. The estimates shown are marginal effects. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Table: D.7: Determinants of the use of surgical and non-surgical contraceptive methods (probit estimates)

	Use of non-surgical methods (dummy)		Use of surgical methods (dummy)	
	Marginal effects	**SE**	**Marginal effects**	**SE**
Uses mobile phone (dummy)	0.057***	(0.008)	-0.047***	(0.008)
Age of respondent (number)	-0.044***	(0.003)	0.054***	(0.002)
Square of age (number)	0.000***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	-0.028***	(0.008)	0.031***	(0.008)
Secondary education (dummy)	0.006	(0.010)	-0.004	(0.011)
Higher education (dummy)	0.065***	(0.013)	-0.075***	(0.014)
Graduate and above (dummy)	0.148***	(0.015)	-0.165***	(0.015)
Mother's education (number)	0.004***	(0.001)	-0.005***	(0.001)
Regular or casual work (dummy)	-0.100***	(0.008)	0.104***	(0.008)
Scheduled caste (dummy)	-0.029***	(0.010)	0.023**	(0.011)
Scheduled tribe (dummy)	-0.042**	(0.017)	0.011	(0.017)
Other backward caste (dummy)	-0.056***	(0.009)	0.061***	(0.009)
Other caste (dummy)	-0.063**	(0.031)	0.053*	(0.032)
Household member (number)	0.011***	(0.001)	-0.010***	(0.001)
Sons alive (number)	-0.036***	(0.004)	0.047***	(0.004)
Household assets (index)	-0.007***	(0.001)	0.007***	(0.001)
Female head (dummy)	-0.011	(0.017)	0.013	(0.017)
Education of head (number)	-0.001	(0.001)	0.001	(0.001)
Age of head (number)	0.001***	(0.000)	-0.001***	(0.000)
Owns BPL card (dummy)	-0.080***	(0.007)	0.072***	(0.007)
Urban region (dummy)	0.069***	(0.011)	-0.064***	(0.011)
District fixed effects	Yes		Yes	
Observations	25,813		25,813	

Note: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Table: D.8: Robustness checks with women's autonomy as additional control variables (full IV model results)

	(1)		(2)		(3)		(4)	
	First stage Uses mobile phone (dummy)		**Second stage Mobility (index)**		**First stage Uses mobile phone (dummy)**		**Second stage Contraceptive use (dummy)**	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)			0.077***	(0.017)			0.195***	(0.028)
Age of respondent (number)	0.016***	(0.001)	0.015***	(0.001)	0.065***	(0.002)	0.062***	(0.002)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	0.018***	(0.004)	0.008	(0.005)	0.044***	(0.006)	0.017**	(0.008)
Secondary education (dummy)	0.027***	(0.005)	0.012*	(0.006)	0.032***	(0.009)	-0.008	(0.011)
Higher education (dummy)	0.051***	(0.006)	0.029***	(0.008)	-0.003	(0.012)	-0.057***	(0.014)
Graduate and above (dummy)	0.062***	(0.008)	0.038***	(0.010)	-0.028**	(0.013)	-0.089***	(0.016)
Mother's education (number)	0.002***	(0.001)	0.002***	(0.001)	0.000	(0.001)	-0.000	(0.001)
Spouse is literate (dummy)	-0.008*	(0.004)	-0.010**	(0.004)				
Financial independence (index)	0.069***	(0.008)	0.059***	(0.008)	0.083***	(0.013)	0.058***	(0.014)
Economic decision (index)	0.024***	(0.005)	0.025***	(0.005)	0.039***	(0.010)	0.038***	(0.010)
Marital harmony (index)	0.054***	(0.004)	0.053***	(0.004)	0.031***	(0.007)	0.031***	(0.007)
Domestic violence [a] (index)	0.037***	(0.007)	0.039***	(0.007)	-0.016	(0.011)	-0.012	(0.011)
Harassment [b](dummy)	0.064***	(0.007)	0.059***	(0.007)	0.093***	(0.014)	0.081***	(0.014)
Scheduled caste (dummy)	-0.001	(0.005)	0.001	(0.005)	0.021**	(0.010)	0.027***	(0.010)
Scheduled tribe (dummy)	0.002	(0.009)	0.003	(0.009)	0.009	(0.015)	0.015	(0.016)
Other backward caste (dummy)	-0.016***	(0.005)	-0.015***	(0.005)	0.020**	(0.009)	0.025***	(0.009)
Other caste (dummy)	-0.046***	(0.012)	-0.046***	(0.012)	-0.002	(0.025)	-0.006	(0.024)
Household members (number)	-0.002*	(0.001)	0.001	(0.001)	0.004***	(0.001)	0.006***	(0.001)
Total Children (number)	0.005***	(0.001)	0.003*	(0.002)				
Sons alive (number)					0.065***	(0.003)	0.063***	(0.003)
Household assets (index)	0.003***	(0.021)	0.002***	(0.000)	0.005***	(0.001)	0.002***	(0.001)
Female head (dummy)	0.068***	(0.000)	0.059***	(0.021)	-0.140***	(0.015)	-0.171***	(0.016)
Education of head (number)	0.000	(0.000)	-0.000	(0.000)	0.001**	(0.001)	0.001	(0.001)
Age of head (number)	-0.000***	(0.003)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Owns BPL card (dummy)	-0.011***	(0.005)	-0.012***	(0.003)	0.006	(0.006)	0.004	(0.007)
Urban region (dummy)	0.032***	(0.001)	0.028***	(0.006)	-0.008	(0.009)	-0.017*	(0.009)
Peer group mobile phone use (#)	0.003***	(0.026)			0.008***	(0.001)		
District fixed effects	Yes		Yes		Yes		Yes	
Constant	0.020		0.054**	(0.026)	-0.988***	(0.056)	-0.906***	(0.056)
Observations	34,427		34,427		34,867		34,867	
First stage F-statistic	461.236***				585.424***			
Test of endogeneity								
Durbin χ^2 statistic	34.033***				67.428***			
Wu-Hausman F- statistic	33.980***				67.390***			

Notes: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level. [a] Higher score implies that the woman feels it is unusual for men to beat their wife in the community she lives in. [b] Binary variable taking the value of 1 if the woman feels it is rare for unmarried girls to be harassed in the neighbourhood.

Table: D.9: Robustness checks with women's access to alternative information sources as additional control variables (full IV model results)

	(1) First stage Uses mobile phone (dummy)		(2) Second stage Mobility(score)		(3) First stage Uses mobile phone (dummy)		(4) Second stage Contraceptive use (dummy)	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)			0.085***	(0.019)			0.202***	(0.029)
Age of respondent (number)	0.019***	(0.001)	0.018***	(0.001)	0.069***	(0.002)	0.065***	(0.002)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	0.018***	(0.004)	0.007	(0.005)	0.041***	(0.007)	0.015*	(0.008)
Secondary education (dummy)	0.026***	(0.005)	0.010	(0.007)	0.031***	(0.009)	-0.008	(0.011)
Higher education (dummy)	0.052***	(0.007)	0.030***	(0.009)	0.001	(0.012)	-0.053***	(0.014)
Graduate and above (dummy)	0.073***	(0.008)	0.046***	(0.010)	-0.011	(0.014)	-0.075***	(0.017)
Mother's education (number)	0.002***	(0.001)	0.002***	(0.001)	0.001	(0.001)	0.000	(0.001)
Spouse is literate (dummy)	-0.006	(0.004)	-0.008*	(0.004)				
Scheduled caste (dummy)	0.004	(0.006)	0.005	(0.006)	0.025**	(0.010)	0.029***	(0.010)
Scheduled tribe (dummy)	0.011	(0.009)	0.012	(0.009)	0.015	(0.016)	0.019	(0.016)
Other backward caste (dummy)	-0.016***	(0.005)	-0.015***	(0.005)	0.021**	(0.009)	0.025***	(0.009)
Other caste (dummy)	-0.049***	(0.012)	-0.050***	(0.012)	-0.004	(0.024)	-0.009	(0.024)
Household members (number)	-0.004***	(0.001)	-0.001	(0.001)	0.002*	(0.001)	0.006***	(0.001)
Household assets (index)	0.003***	(0.000)	0.002***	(0.000)	0.066***	(0.003)	0.064***	(0.003)
Female head(dummy)	0.062***	(0.022)	0.052**	(0.022)	0.003***	(0.001)	0.001	(0.001)
Education of head (number)	-0.000	(0.000)	-0.000	(0.000)	-0.134***	(0.016)	-0.167***	(0.016)
Age of head (number)	-0.001***	(0.000)	-0.001***	(0.000)	0.001**	(0.001)	0.001	(0.001)
Owns BPL card (dummy)	-0.013***	(0.004)	-0.015***	(0.004)	-0.001***	(0.000)	-0.001***	(0.000)
Total Children (number)	0.008***	(0.001)	0.004***	(0.002)	0.004	(0.006)	0.003	(0.007)
Women listen to radio (dummy)	0.002	(0.004)	-0.003	(0.004)	-0.005	(0.007)	-0.019**	(0.008)
Women watch TV (dummy)	0.001	(0.005)	-0.001	(0.005)	0.054***	(0.009)	0.049***	(0.009)
Women read newspaper (dummy)	0.011***	(0.004)	0.008**	(0.004)	-0.002	(0.007)	-0.007	(0.007)
Urban region (dummy)	0.027***	(0.006)	0.023***	(0.006)	-0.013	(0.009)	-0.021**	(0.009)
Peer group mobile phone use (#)	0.004***	(0.001)			0.008***	(0.001)		
District fixed effects	Yes		Yes		Yes		Yes	
Constant	0.143***	(0.026)	0.176***	(0.025)	-0.895***	(0.057)	-0.820***	(0.056)
Observations	34,480		34,480		34,918		34,918	
First stage F-statistic	444.831***				573.069***			
<u>Test of endogeneity</u>								
Durbin χ^2 statistic	37.815***				68.916***			
Wu-Hausman F- statistic	37.761***				68.885***			

Notes: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Table: D.10: Effects of mobile phone use on women's mobility in poor and non-poor households (full IV model results)

	(1)		(2)		(3)		(4)	
	First stage		Second stage		First stage		Second stage	
	Uses mobile phone (dummy)		Mobility (index)		Uses mobile phone (dummy)		Mobility (index)	
	Poor				Non-poor			
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)			0.133***	(0.033)			0.077***	(0.020)
Age of respondent (number)	0.014***	(0.004)	0.012***	(0.002)	0.019***	(0.002)	0.019***	(0.001)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Primary education (dummy)	0.092***	(0.015)	0.001	(0.009)	0.146***	(0.009)	0.009	(0.006)
Secondary education (dummy)	0.159***	(0.024)	0.013	(0.014)	0.206***	(0.011)	0.012*	(0.007)
Higher education (dummy)	0.243***	(0.041)	0.011	(0.022)	0.286***	(0.014)	0.034***	(0.009)
Graduate and above (dummy)	0.248***	(0.066)	0.038	(0.032)	0.337***	(0.014)	0.050***	(0.011)
Mother's education (number)	-0.001	(0.003)	0.001	(0.002)	0.002**	(0.001)	0.002***	(0.001)
Spouse is literate (dummy)	0.012	(0.014)	-0.014	(0.009)	0.029***	(0.009)	-0.006	(0.005)
Scheduled caste (dummy)	-0.016	(0.019)	0.026**	(0.011)	-0.009	(0.010)	-0.001	(0.006)
Scheduled tribe (dummy)	-0.022	(0.022)	0.026	(0.016)	-0.001	(0.015)	0.004	(0.009)
Other backward caste (dummy)	0.009	(0.019)	0.006	(0.011)	-0.017**	(0.009)	-0.020***	(0.005)
Other caste (dummy)	-0.015	(0.062)	-0.041	(0.031)	0.016	(0.027)	-0.053***	(0.012)
Household members (number)	-0.024***	(0.004)	-0.004**	(0.002)	-0.031***	(0.002)	-0.001	(0.001)
Total Children (number)	0.026***	(0.005)	0.002	(0.003)	0.042***	(0.003)	0.005***	(0.002)
Household assets (index)	0.016***	(0.002)	-0.000	(0.001)	0.012***	(0.001)	0.003***	(0.001)
Female head (dummy)	0.085	(0.075)	0.067	(0.042)	0.131**	(0.056)	0.048*	(0.026)
Education of head (number)	0.002	(0.002)	0.001	(0.001)	0.002**	(0.001)	-0.000	(0.000)
Age of head (number)	0.001	(0.001)	-0.001***	(0.000)	0.001**	(0.000)	-0.001***	(0.000)
Urban region (dummy)	0.039**	(0.019)	0.034***	(0.011)	0.054***	(0.011)	0.023***	(0.006)
Peer group mobile phone use (#)	0.035***	(0.003)			0.044***	(0.002)		
District fixed effects	Yes		Yes		Yes		Yes	
Constant	-0.386***	(0.088)	0.320***	(0.053)	-0.402***	(0.046)	0.139***	(0.026)
Observations	5,945		5,945		28,550		28,550	
First stage F-statistic	165.907***				409.236***			
Test of endogeneity								
Durbin χ^2 statistic	15.927***				24.341***			
Wu-Hausman F- statistic	15.749***				24.291***			

Notes: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Table: D.11: Effects of mobile phone use on women's mobility in purdah and non-purdah households (full IV model results)

	(1) First stage		(2) Second stage		(3) First stage		(4) Second stage	
	Uses mobile phone (dummy)		**Mobility (index)**		**Uses mobile phone (dummy)**		**Mobility (index)**	
	Purdah				**Non-purdah**			
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)			0.093***	(0.027)			0.084***	(0.022)
Age of respondent (number)	0.019***	(0.002)	0.018***	(0.001)	0.014***	(0.003)	0.018***	(0.001)
Square of age (number)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Primary education (dummy)	0.151***	(0.009)	0.011*	(0.007)	0.111***	(0.012)	0.004	(0.006)
Secondary education (dummy)	0.206***	(0.013)	0.014	(0.009)	0.185***	(0.015)	0.011	(0.008)
Higher education (dummy)	0.294***	(0.018)	0.040***	(0.013)	0.256***	(0.018)	0.023**	(0.011)
Graduate and above (dummy)	0.324***	(0.019)	0.056***	(0.015)	0.316***	(0.020)	0.040***	(0.012)
Mother's education (number)	0.002	(0.001)	0.001	(0.001)	0.002	(0.001)	0.002***	(0.001)
Spouse is literate (dummy)	0.023**	(0.010)	-0.009	(0.006)	0.025*	(0.013)	-0.010	(0.007)
Scheduled caste (dummy)	-0.019	(0.012)	0.024***	(0.007)	-0.013	(0.014)	-0.027***	(0.008)
Scheduled tribe (dummy)	-0.032**	(0.016)	0.024**	(0.012)	-0.005	(0.018)	-0.015	(0.012)
Other backward caste (dummy)	-0.012	(0.010)	0.006	(0.006)	-0.020	(0.012)	-0.044***	(0.007)
Other caste (dummy)	0.029	(0.034)	-0.029	(0.018)	-0.014	(0.034)	-0.068***	(0.014)
Household members (number)	-0.033***	(0.002)	-0.002	(0.001)	-0.026***	(0.003)	-0.000	(0.002)
Total Children (number)	0.042***	(0.003)	0.003	(0.002)	0.029***	(0.005)	0.005**	(0.002)
Household assets (index)	0.014***	(0.001)	0.002***	(0.001)	0.013***	(0.001)	0.001**	(0.001)
Female head (dummy)	0.106	(0.073)	0.090***	(0.029)	0.137**	(0.061)	0.020	(0.028)
Education of head (number)	0.002**	(0.001)	-0.000	(0.001)	0.003**	(0.001)	-0.000	(0.001)
Age of head (number)	0.000	(0.000)	-0.001***	(0.000)	0.001**	(0.000)	-0.001**	(0.000)
Owns BPL card (dummy)	0.007	(0.008)	-0.004	(0.004)	0.023**	(0.010)	-0.026***	(0.005)
Urban region (dummy)	0.046***	(0.013)	0.024***	(0.008)	0.051***	(0.014)	0.018**	(0.008)
Peer group mobile phone use (#)	0.036***	(0.002)			0.053***	(0.002)		
District fixed effects	Yes		Yes		Yes		Yes	
Constant	-0.447***	(0.065)	0.128***	(0.034)	-0.334***	(0.062)	0.219***	(0.034)
Observations	20,209		20,209		14,282		14,282	
First stage F-statistic	237.289***				501.039***			
Test of endogeneity								
Durbin χ^2 statistic	22.349***				19.052***			
Wu-Hausman F- statistic	22.282***				18.969***			

Notes: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Table: D.12: Effects of mobile phone use on women's use of contraceptives in poor and non-poor households (full IV model results)

	(1) First stage		(2) Second stage		(3) First stage		(4) Second stage	
	Uses mobile phone (dummy)		Uses contraceptives (dummy)		Uses mobile phone (dummy)		Uses contraceptives (dummy)	
	Poor				Non-poor			
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Uses mobile phone (dummy)			0.209***	(0.063)			0.199***	(0.030)
Age of respondent (number)	0.018***	(0.003)	0.059***	(0.005)	0.020***	(0.002)	0.064***	(0.002)
Square of age (number)	-0.000***	(0.000)	-0.001***	(0.000)	-0.000***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	0.090***	(0.014)	0.035**	(0.015)	0.150***	(0.008)	0.014	(0.009)
Secondary education (dummy)	0.151***	(0.023)	0.011	(0.025)	0.214***	(0.010)	-0.007	(0.012)
Higher education (dummy)	0.219***	(0.039)	-0.102**	(0.045)	0.285***	(0.013)	-0.050***	(0.015)
Graduate and above (dummy)	0.276***	(0.062)	-0.061	(0.064)	0.330***	(0.013)	-0.085***	(0.017)
Mother's education (number)	-0.001	(0.003)	0.004	(0.003)	0.002*	(0.001)	-0.000	(0.001)
Regular or casual work (dummy)	0.007	(0.012)	0.067***	(0.014)	0.046***	(0.007)	0.048***	(0.008)
Scheduled caste (dummy)	-0.021	(0.019)	0.045**	(0.023)	-0.024**	(0.010)	0.016	(0.010)
Scheduled tribe (dummy)	-0.030	(0.022)	0.026	(0.029)	-0.019	(0.014)	-0.001	(0.017)
Other backward caste (dummy)	0.009	(0.018)	0.026	(0.022)	-0.021**	(0.008)	0.022**	(0.009)
Other caste (dummy)	-0.025	(0.061)	0.062	(0.069)	0.005	(0.026)	-0.018	(0.024)
Household members (number)	-0.014***	(0.002)	-0.006*	(0.003)	-0.015***	(0.001)	0.008***	(0.002)
Sons alive (number)	0.013***	(0.005)	0.048***	(0.006)	0.007**	(0.003)	0.070***	(0.004)
Household assets (index)	0.016***	(0.001)	0.006***	(0.002)	0.013***	(0.001)	0.003***	(0.001)
Female head (dummy)	0.051**	(0.020)	-0.211***	(0.041)	0.130***	(0.010)	-0.162***	(0.017)
Education of head (number)	0.002	(0.002)	0.000	(0.002)	0.004***	(0.001)	0.001	(0.001)
Age of head (number)	0.001	(0.001)	-0.001*	(0.001)	0.001**	(0.000)	-0.002***	(0.000)
Owns BPL card (dummy)	-0.003	(0.011)	-0.002	(0.012)	0.011	(0.007)	-0.000	(0.007)
Urban region (dummy)	0.036**	(0.018)	-0.033*	(0.020)	0.048***	(0.011)	-0.016*	(0.009)
Peer group mobile use (#)	0.033***	(0.003)			0.041***	(0.002)		
District fixed effects	Yes		Yes		Yes		Yes	
Constant	-0.440***	(0.084)	-0.701***	(0.123)	-0.375***	(0.044)	-0.820***	(0.058)
Observations	6,751		5,977		32,551		28,934	
First stage F-statistic	143.189***				561.538***			
Test of endogeneity								
Durbin χ^2 statistic	9.923***				58.412***			
Wu-Hausman F- statistic	9.801***				58.362***			

Notes: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.

Table: D.13: Effects of mobile phone use on women's use of contraceptives in purdah and non-purdah households (full IV model results)

	(1) First stage		(2) Second stage		(3) First stage		(4) Second stage	
	Uses mobile phone (dummy)		**Uses contraceptives (dummy)**		**Uses mobile phone (dummy)**		**Uses contraceptives (dummy)**	
	Purdah				**Non-purdah**			
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Uses mobile phone (dummy)			0.180***	(0.042)			0.229***	(0.032)
Age of respondent (number)	0.021***	(0.002)	0.067***	(0.003)	0.016***	(0.002)	0.057***	(0.003)
Square of age (number)	-0.000***	(0.000)	-0.001***	(0.000)	-0.000***	(0.000)	-0.001***	(0.000)
Primary education (dummy)	0.148***	(0.009)	0.020*	(0.011)	0.126***	(0.011)	0.002	(0.011)
Secondary education (dummy)	0.205***	(0.013)	-0.015	(0.016)	0.205***	(0.014)	-0.014	(0.014)
Higher education (dummy)	0.280***	(0.017)	-0.084***	(0.021)	0.271***	(0.018)	-0.045**	(0.020)
Graduate and above (dummy)	0.312***	(0.018)	-0.085***	(0.024)	0.323***	(0.019)	-0.093***	(0.022)
Mother's education (number)	0.002	(0.001)	0.002	(0.001)	0.001	(0.001)	-0.002	(0.001)
Regular or casual work (dummy)	0.018**	(0.009)	0.062***	(0.009)	0.048***	(0.009)	0.030***	(0.010)
Scheduled caste (dummy)	-0.026**	(0.011)	0.018	(0.013)	-0.024*	(0.014)	0.023*	(0.013)
Scheduled tribe (dummy)	-0.049***	(0.016)	0.015	(0.021)	-0.006	(0.018)	-0.019	(0.022)
Other backward caste (dummy)	-0.014	(0.010)	0.016	(0.012)	-0.021*	(0.012)	0.031***	(0.011)
Other caste (dummy)	0.028	(0.032)	-0.040	(0.040)	-0.025	(0.034)	0.016	(0.027)
Household members (number)	-0.016***	(0.001)	0.004**	(0.002)	-0.015***	(0.002)	0.012***	(0.002)
Sons alive (number)	0.010***	(0.003)	0.065***	(0.004)	0.005	(0.004)	0.071***	(0.005)
Household assets (index)	0.014***	(0.001)	0.004***	(0.001)	0.013***	(0.001)	-0.000	(0.001)
Female head (dummy)	0.105***	(0.012)	-0.133***	(0.020)	0.136***	(0.014)	-0.230***	(0.027)
Education of head (number)	0.003***	(0.001)	0.002*	(0.001)	0.004***	(0.001)	0.001	(0.001)
Age of head (number)	0.000	(0.000)	-0.001***	(0.000)	0.001***	(0.000)	-0.002***	(0.000)
Owns BPL card (dummy)	0.001	(0.007)	-0.001	(0.008)	0.019**	(0.010)	-0.006	(0.010)
Urban region (dummy)	0.039***	(0.013)	-0.028**	(0.012)	0.049***	(0.014)	-0.013	(0.012)
Peer group mobile phone use (#)	0.034***	(0.002)			0.049***	(0.002)		
District fixed effects	Yes		Yes		Yes		Yes	
Constant	-0.431***	(0.063)	-0.685***	(0.078)	-0.374***	(0.059)	-0.693***	(0.078)
Observations	22,972		20,544		16,337		14,374	
First stage F-statistic	301.976***				451.894***			
Test of endogeneity								
Durbin χ^2 statistic	24.596***				50.022***			
Wu-Hausman F- statistic	24.526***				49.910***			

Notes: Standard errors are clustered at the village level. * Significant at 10% level, ** Significant at 5% level, ***Significant at 1% level.