Is IT Enough? Evidence from a Natural Experiment in India's Agriculture Markets

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Access to information and communication technologies (ICTs) such as mobile phone networks is widely known to improve market efficiency. In this paper, we examine whether access to timely and accurate information provided through ICT applications has any additional impact. Using a detailed dataset from Reuters Market Light (RML), a text message service in India that provides daily price information to farmers, we find that this information reduces geographic price dispersion of crops in rural communities by as much as 5.2% (std. error 2.6%, p-value 4.5%), over and above access to mobile phone technology and other means of communication. To identify the effect of information on price dispersion we exploit a natural experiment where bulk text messages were banned unexpectedly across India for twelve days in 2010. We find that access to RML information has the highest impact in areas where RML has the largest number of subscribers. Also, the effect is largest for perishable crops. RML thus reduces the higher risk associated with high value perishable crops. We discuss implications for development organizations and for information providers.

Key words: price dispersion, information and communication technology, natural experiment, supply chains

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1. Introduction

The rapid and widespread growth of information and communication infrastructure such as mobile phone networks in Africa and Asia has created a number of opportunities for economic growth and development (Aker and Mbiti 2010, Mittal et al. 2010). New technologies often create new ways to gather the information necessary to make economic decisions. For example, farmers and fishermen in rural areas of the developing world use mobile phones to access information on the price of agricultural commodities in local markets (see review by Jensen 2010). By reducing the cost of access to such information, new Information and Communication Technologies (ICTs) enable farmers to make better decisions on where to sell their produce - shifting supply from low to high price markets, as well as when to sell it - delaying or bringing forward the harvesting or selling of crops to exploit price variation over time. Reducing the cost of acquiring such information should in theory yield a more precise matching of supply and demand and therefore result in more efficient markets and less variation in prices. Indeed, two recent studies report that the improved information flow associated with the introduction of mobile phone coverage causes a permanent decrease in geographic price dispersion of fish in Kerala, India (Jensen 2007) and grain in Niger (Aker 2010).

Research to date implicitly assumes that the primary barrier to information acquisition is the prohibitive cost of communication, i.e. once communication costs are reduced by novel ICTs then information becomes readily available, which in turn causes a permanent reduction in price dispersion. Of course being able to communicate cheaply does help with information acquisition, but is it sufficient? It is possible that farmers living in small rural communities may have easier access to affordable mobile phone networks than to informed and unbiased parties from whom they can obtain timely and accurate information. The primary goal of this study is to empirically investigate whether the existence of a third-party information provider, on which farmers can rely for timely and accurate information transmitted through the ICT infrastructure, has an impact on the matching of supply and demand of agricultural commodities, over and above the now widely recognized impact of having access to an ICT.

This is an important question because substantial resources are being invested in order to improve the efficiency of agricultural supply chains in the developing world. For example, the World Bank invested \$4.2 billion in the developing world's ICT infrastructure between 2003 and 2010 (World Bank 2011). Most of this funding has been used to improve access to ICTs such as mobile phone networks, and for good reason. Despite widespread press coverage on the use of mobile phones in Africa and Asia (e.g. The Economist 2011) the technology's penetration levels in the developing world remain low. For example, in rural India it is estimated to be as low as 23% (The Hindu 2011). To foster the welfare improvements that result from greater market efficiency (Jensen 2007), should governments and funding agencies continue to invest heavily in improving ICT infrastructure in developing nations, or should they complement this investment with funding for third party ICT applications which provide reliable and up-to-date information to market participants?

To answer this question we use a detailed dataset from Reuters Market Light (RML), a commercial third party information provider wholly owned by Thomson Reuters. RML provides information on the price of agricultural commodities in India via mobile phone text messages sent daily to its paying subscribers. We hypothesize that by providing this information, RML allows for a better match of supply and demand in individual markets, leading to lower levels of geographic price dispersion than would be obtained simply due to having access to ICT infrastructure. However, measuring this effect is an econometrically challenging problem. Since neither RML managers, nor RML customers choose randomly where to offer or acquire the service, a potentially serious source of endogeneity could be present. If the benefit of having access to accurate price information is greatest in areas with chronically high price dispersion, one might expect these to be the areas where RML has the most subscribers. By simply comparing price dispersion in areas where RML has a high number of subscribers to areas where it does not, one would likely underestimate the reduction in price dispersion due to RML, or indeed, find that RML is associated with higher price dispersion. One possible solution to this potential endogeneity problem is to perform a randomized controlled experiment. However, such an experiment would be expensive and disruptive to organize as it would require a sizeable experimental intervention, where some areas are randomly chosen to receive RML coverage and others are not. Further, the inevitable sharing of RML information with neighbors, family and friends could contaminate the control group. Instead, to overcome this problem we exploit a natural experiment.

On September 23, 2010, RML experienced a major service disruption when all bulk text messages were unexpectedly banned throughout India in advance of a High Court verdict that was to be announced on September 24. The case in question was a land title dispute for a site in the city of Ayodhya in Uttar Pradesh, India that has religious significance for both Hindus and Muslims. Deadly protests and political unrest surround the history of the site. In an attempt to reduce the likelihood of rumors spreading via text message and technologically coordinated riots, the Ministry of Communications & Information Technology of the Government of India directed telecommunication providers to immediately disable bulk text messages throughout India on the evening of September 22, 2010. The ban was lifted on the night of October 4, 2010 and operations at RML returned to normal on October 5, 2010. For the twelve days of the ban, RML collected price information without being able to transmit it.

The bulk text message ban was an unexpected, exogenous shock, completely unrelated to prices except through the information provided by RML. All other sources of information retrieval, including visiting or placing phone calls to markets, sending personal text messages, asking friends, family and fellow market participants, or even checking prices through the Internet were still available. This provides an almost ideal natural experiment econometric specification which removes most concerns regarding endogeneity. Using a powerful market-cluster fixed effect formulation to control for market heterogeneity, as well as a two-dimensional robust error structure that allows for arbitrary correlations within crops over time and correlation across crops on the same day, we find that the average geographic price dispersion, measured as the standard deviation of the price of a crop in all markets open in a state (which we call a crop-market-cluster) on any given day (averaged over 170 crops and 13 states) increased by 5.2% (std. error 2.6%, p-value 4.5%) during the ban as compared to the period before the ban. When the ban was lifted, price dispersion returned to pre-ban levels. The largest price dispersion increase during the ban was observed in the groups of markets where RML had the largest number of subscribers, providing further evidence that the increase in price dispersion was caused by the loss of RML information. Further, we find no evidence to suggest that the events surrounding the Ayodhya verdict had any direct effect on price dispersion other than through the ban. Namely, we find no difference in volumes or prices transacted during the ban, or any measurable difference in price dispersion between those states with high muslim populations, where religious tensions were likely to have been most significant, and those states with low muslim populations.

Unlike in developed countries where electronic markets are predominant, gathering price data in developing countries can be challenging. For this reason, most studies to date on the impact of information on market efficiency in agricultural supply chains have focused on a single crop. Yet an important question is whether access to timely and accurate information is of equal value for all crops, or more important for some than for others. While crops differ in myriad ways, perishability is a critical crop characteristic from the perspective of supply chain economics. Perishable crops are often more expensive to store and transport, and typically command higher profit margins (Joshi et al. 2006, Mittal 2007). Policy makers have suggested that farmers can increase their incomes by growing higher value crops such as fruits and vegetables in addition to long-lasting staples such as rice and wheat (Sanchez and Swaminathan 2005). However, perishables are also considered more risky, as they are more prone to weather damage, may have more volatile prices, and cannot be stored easily (Joshi et al. 2006).

If access to better information reduces the risk associated with perishables, providing such access should eventually enable farmers to diversify into more profitable crops. So a critical question is whether access to better information results in a greater reduction in price dispersion for perishables than for non-perishables. A few very recent studies have attempted to examine this question. However, due to the severe data limitations, such studies were limited to just two crops. The richness of our dataset allows us to investigate the impact of perishability using 170 different crops. We find that both highly perishable crops (such as bananas, coriander or okra) and crops with intermediate perishability (such as apples or pomegranates) exhibit lower price dispersion when price information is available via RML, lending support to the hypothesis that the information provided by RML reduces the risk associated with these higher margin crops. Conversely, we find that low perishability crops (such as wheat, soybeans or lentils) are not impacted.

Since we find that the information provided by RML is effective in reducing price dispersion only when the markets open within a state have a relatively high number of subscribers, a natural follow-up question is whether these high subscription markets are systematically different to those with a low number of subscribers. Being able to answer this question has important implications. If we find that there is no systematic difference in such markets then one would expect RML subscriptions to increase over time, eventually resulting in lower price dispersion in these markets as well. To understand if there are any systematic differences we compare the inter-market distance composition of the high-subscription market clusters to the low-subscription market clusters. We find that on this distance-based measure a little over 55% of low-subscriber market clusters are systematically different to the high-subscriber ones. The remaining 45% of the low-subscriber market clusters have similar enough inter-market distance distribution to suggest that they have the potential to become high subscriber markets.

In summary, we make three contributions. First, we utilize a novel identification strategy, namely a natural experiment, to overcome the endogeneity concerns inherent in any econometric study (cf. Aker 2008, Jensen 2007) that seeks to identify the impact of a new information technology on price dispersion. Second, we contribute to the literature on how ICTs impact rural supply chains in the developing world. We show that access to ICTs alone is not by itself sufficient to completely eliminate informational frictions. Access to timely and accurate information provided via ICT applications results in reductions in price dispersion that amount to 25 to 50% of the reductions due to access to mobile phone networks and other ICT infrastructure alone. Third, our research also sheds light on how information impacts markets for crops with different perishability levels, a question that previous research has addressed inconclusively due to data limitations (Aker and Fafchamps 2010), as well as how markets with a high number of subscribers differ in their inter-market distance composition to markets with a low number of subscribers.

Our work has several further managerial and policy implications. On the managerial side, it provides support for the business model of third party information providers, such as RML, by showing that they make a significant difference to the functioning of agricultural crop markets in the developing world. It is therefore understandable that this business model is proliferating.[1] Our research also provides specific advice on which types of crops – in terms of perishability – and what kinds of market clusters – in terms of inter-market distance composition – such information aggregation services should target to provide the largest benefit to their customers. This can help such organizations focus their operational and marketing efforts, as well as inform development organizations as to what types of crops to target for funding.

[1] A number of initiatives, such as RML, that aim to provide rural farmers and fishermen with price and advisory information are being introduced both in India and other developing countries. Examples in India include IKSL, a partnership between the Indian Farmers Fertilisers Cooperatives and Bharti Airtel, an Indian mobile operator (Mittal et al. 2010), Fisher Friend, a program funded by an NGO in partnership with Qualcomm, an international technology company, and Tata Teleservices, an Indian mobile operator (Mittal et al. 2010), and Nokia Life tools, a service offered by Nokia, a European handset maker (`http://www.nokia.com/NOKIA_COM_1/Microsites/Entry_Event/phones/Nokia_Life_Tools_datasheet.pdf`, accessed June 29, 2012). Examples in Western Africa include Esoco, a private for-profit company which receives funding from USAID (see USAID 2010) and Manobi, another private for-profit company which works in partnership with Sonatel, a mobile phone operator (see `http://www.manobi.net`, accessed June 29, 2012). Other third party initiatives that combine information services with a platform that facilitates exchange include Google Trader, a partnership between Google, the Internet search provider, and MTN, a mobile phone operator, which operates in Uganda and Ghana (`http://www.google.co.ug/africa/trader/home`, accessed June 29, 2012), and CellBazar in Bangladesh (`http://corp.cellbazaar.com`, accessed June 29, 2012).

2. Literature Review

The "law of one price" predicts that prices of homogeneous goods exchanged simultaneously in open markets at different locations should not differ by more than transportation costs (Isard 1977). Yet, many studies empirically document the existence of price dispersion, while others provide analytical models which identify sufficient conditions – such as search costs – under which it is an equilibrium outcome. Baye et al. (2006) provides an excellent review of this literature.

Our study complements a subset of this literature that investigates the impact of new ICTs on price dispersion in general and on price dispersion of agricultural commodities in the developing world in particular. This line of research presents the argument that successive generations of ICT, such as the telegraph, telephone lines, and more recently mobile phones and the Internet, have transformed markets by reducing search costs (Malone et al. 1987, Bakos 1991, 1997, Harrington 2001). The literature examines whether prices, and more importantly for our purposes, price dispersion, are affected as newer technologies are introduced.[2]

Previous research has highlighted the role of ICTs and ICT-enabled services in reducing price dispersion. Brynjolfsson and Smith (2000) compare the price dispersion of CDs and books sold via physical sales channels vs. Internet channels, and report lower prices and lower price dispersion in online channels. Tang et al. (2010) find that a 1% increase in the use of Internet-enabled real-time price comparison algorithms – shopbots – decreases price dispersion by 1%. Shopbots act as independent aggregators of price information in a similar way that RML provides price information. Overby and Forman (2011) demonstrate that the use of electronic channels alongside physical channels for selling used vehicles reduces geographic price dispersion. Ghose and Yao (2011) use transaction instead of posted prices to show that electronic markets nearly obey the "law of one price."

Nevertheless, there is ample evidence to suggest that the advent of new ICTs does not completely eliminate price dispersion. Gatti and Kattuman (2003) measure the online price dispersion of 31 products across seven European countries and find significant price dispersion both between countries and across product categories, such as printers or computer games. Baye et al. (2004) report significant price variation for consumer electronics sold online. Explanations put forward to explain persistent price dispersion include consumers' failure to compare prices even when search costs are small (Baye and Morgan 2001), bounded rationality (Baye et al. 2004), consumers' failure to internalize additional costs such as shipping fees (Einav et al. 2011) or firms' use of "obfuscation strategies" such as bait-and-switch (Ellison and Ellison 2005, 2009).

[2] Note that not all theoretical models of price dispersion agree that a reduction in search costs will result in lower price dispersion (e.g. MacMinn 1980). However, in economic search models of agricultural commodities (see Jensen 2007, Aker 2010) the theoretical prediction is that a reduction in search costs will reduce geographic price dispersion.

Since price dispersion is so pervasive despite advances in ICT, it is not surprising that we find significant geographic price dispersion for agricultural commodities in India. Importantly, we show that in the absence of the additional benefit of high quality information provided by ICT applications such as RML over and above access to an ICT, price dispersion is even higher. Our paper can be interpreted in a manner similar to Tang et al. (2010) in that we measure the benefit of timely and acurate information delivered to farmers over and above access to mobile phones, while Tang et al. (2010) examine the benefit of timely and accurate information delivered via automated shopbots to consumers over and above access to the Internet.

A few recent studies have examined the impact of mobile phones on the price dispersion of agricultural goods. Jensen (2007) examines fish markets in Kerala, India before and after the introduction of mobile phones. He presents an impressive measurement of welfare gains from the introduction of the technology. One of the main sources of gain was the dramatic and permanent reduction in geographic price dispersion that occurred after the introduction of mobile phones. Aker (2010) reports that the introduction of mobile phones in Niger resulted in a 10% decrease in price dispersion across grain markets. Both studies exploit the quasi-experimental staggered introduction of mobile phones for empirical identification. Our research contributes to this stream by demonstrating that having access to an independent and reliable information provider can further reduce price dispersion, over and above the gains of having access to a mobile phone. Also, our natural experiment identification strategy provides further evidence on the benefit of ICT use on geographic price dispersion in agricultural supply chains. Unlike previous studies, we do not need to rely on the quasi-experimental roll out of mobile phones to identify the impact.

Aker and Fafchamps (2010) use a similar dataset to Aker (2010) to compare the impact of introducing mobile phones on the price dispersion of a semi-perishable crop (cowpeas) and a storable crop (millet). They find that the impact of having access to mobile phones reduces dispersion for the semi-perishable crop by 6.3%, while it does not have any measurable effect on the storable crop. They find that this effect is concentrated in off-season crops in markets that are over 350 kilometers apart and linked by unpaved roads. We complement their study by examining a range of different crops. This allows us to verify that differences in price dispersion reductions caused by mobile phone access attributed to differences in crop perishability in previous studies are not due to unobserved differences between the specific one or two crops studied.

Other studies attempt to investigate the impact of ICTs on prices received by farmers, but do not in general investigate the impact on price dispersion. The results are somewhat mixed. Goyal (2010) studies the impact of the introduction of Internet kiosks on soybean prices in the Indian state of Madhya Pradesh. The kiosks were introduced by the India Tobacco Company, a large conglomerate that also purchases soybeans. Besides offering information about the price of soya in local and wholesale markets through its "e-Choupal" program, it also offers farmers the option to sell directly to the company at a pre-agreed price and quality (Devalkar et al. 2011). Goyal (2010) reports a 1.9% increase in soybean prices for farmers. Svensson and Yanagizawa (2009) examine the impact of a different ICT application, a radio program that provides Ugandan farmers with market data. They report a 15% increase in the price received by maize farmers with radios in areas where the service is offered. In contrast to these studies, Fafchamps and Minten (2012) work with Thomson Reuters to conduct a randomized experiment where they give the RML service to farmers in some villages in Maharashtra but not to others, over the period of a year. While the farmers claimed to have used the RML information, there is no statistical evidence that RML influenced the income of the farmers that were using it. Similarly, Futch and McIntosh (2009) report no effect on the income of farmers from the introduction of a village phone program in Rwanda. In contrast to these studies, we aim to measure aggregate market efficiency as measured by geographic price dispersion.

3. Empirical Setting

Below we provide a brief introduction to India's agricultural sector, as well as information on the service offered by RML and a description of the natural experiment we utilize to identify the impact of information on price dispersion. Our understanding of the empirical setting was enriched by personal observation and primary data collected by the authors between January 2009 and December 2010 through site visits and interviews with RML employees, agricultural experts, farmers, traders and government officials.

3.1. Indian Agricultural Markets and Supply Chain

The Indian agriculture sector plays a key role in the country's economy (e.g. World Bank 2008). It is estimated to make up 18.1% of the national GDP and it employs an estimated 52% of the labor force (Central Intelligence Agency 2012). An estimated 455.8 million Indians live in agricultural households, on incomes below the World Bank's official poverty line of $1.25 a day (Chen and Ravallion 2008, Table 6). Given the size and extreme poverty of this sector, even a modest efficiency improvement will have a drastic effect on welfare and can go a long way towards reducing poverty, one of the key Millennium Development Goals of the United Nations.[3]

To prevent farmers from being exploited and help them sell their produce at a fair price, the markets for agricultural produce in India are regulated through the Agricultural Produce Marketing (APM) Act. The APM Act requires states to regulate spot markets for agricultural produce, called "mandis". At the local level, this regulation is the responsibility of the Agricultural Produce

[3] See `http://www.un.org/millenniumgoals/` (accessed June 29, 2012) for more information on the Millennium Development Goals.

Marketing Committees (APMCs), which decide where to establish markets and are responsible for their day-to-day operations. In particular, APMCs are responsible for licensing and regulating all traders that are allowed to operate within these markets, as well as setting the rules for and overseeing the completion of all market transactions (Thomas 2003).

The APMC regulated mandis are either auction or terminal markets. In auction markets, which tend to be smaller than terminal markets, farmers sell directly to traders through auctioneers who are either APMC employees or commission agents hired by farmers. Auctioneers are responsible for conducting auctions, weighing produce and coordinating payment and delivery. On arrival at a market, a farmer is assigned a number, and waits in the corresponding parking spot. The auctioneer, along with an administrator, leads traders from truck to truck, holding auctions for goods as they progress. The goods are presented and bid on by the traders in an open outcry, ascending first price or English auction. The produce is then weighed and the farmer is paid according to the price set in the auction. Produce purchased in auction markets is sorted, packaged and shipped to either domestic markets, which are called terminal markets, or international destinations. In terminal markets, traders sell large quantities to wholesalers, retailers and sometimes to end consumers. The trader sets a price and buyers visit different traders' stalls to barter for goods.

3.2. Reuters Market Light (RML)

RML is a fully owned subsidiary of Thompson Reuters based in India. It was launched in October 2007 to offer highly personalized information to farmers via daily text messages through the existing mobile phone infrastructure. For a subscription fee of approximately Rs. 80 ($2) per month, RML provides information on local market prices and volumes transacted, highly localized weather forecasts and crop-specific advisory (such as which fertilizer to use or how deep to plant specific seed varieties), as well as national and international news stories related to agriculture (Velu and Prakash 2010, Markides 2009).

Subscribing to RML is a relatively simple process. Prospective subscribers purchase a subscription card from RML's local distributors, such as agricultural supplies stores. To activate a three, six or twelve month subscription the subscriber must call RML's dedicated call center, and select two crops and three markets for each crop for which she will receive price/volume information, her local taluka (similar to a US county) for which she will receive weather forecasts, and one of nine languages (Bengali, English, Gujarati, Hindi, Kannada, Marathi, Punjabi, Tamil and Telugu) for the text messages she receives. The subscriber begins receiving RML text messages within two days of activating the subscription.

To gather the price and volume information, RML dispatches a market reporter to each market it covers on every day the market is open. The market reporter records the high and low price of the day, as well as the volume transacted for the highest quality grade of each commodity. In auction markets this is done by simply observing the daily auctions, while in terminal markets the market reporter visits each of the individual traders' stalls. The high and low price are not actually the highest and lowest prices observed during the day but the 95th and 5th percentile of the distribution of prices. RML records this information since it is often more stable and therefore a better indication of prices than the highest and lowest prices. Throughout the paper we use the high and low price terminology adopted by RML. The market reporter confirms the price and volume information collected with the APMC officials at the market and transmits this information either via voice call or text message to the central RML system. The information is first validated by an automated system which flags any obvious errors such as typos or unusual price patterns. A chief market reporter then independently checks the prices for several markets and resolves any discrepancies with the relevant market reporter, before submitting the final price and volume information to the system. This information is then relayed to subscribers via bulk text messages. The time of day that price text messages are sent to the farmer depends on the crop. Depending on timing, the information is actionable on the day it is received or the following day. It is worth emphasizing that the system only collects and reports prices for produce of the highest quality. Farmers with lower quality produce can expect to receive lower prices.

As of December 2011, RML provides coverage on 250 crops and 1,000 local markets across 13 states and claims one million unique subscribers in 40,000 talukas.[4] In recognition of its contribution to India's agriculture markets, the service has won a number of awards, including the 2010 Rural Marketing Association of India award for the best Internet/SMS/mobile initiative and the 2010 World Business and Development Award (WBDA) conferred by the United Nations Development Programme, the International Chamber of Commerce and the International Business Leaders Forum.[5]

3.3. The Natural Experiment

Ayodhya, a city in the northern Indian state of Uttar Pradesh, is at the center of a centuries old religious dispute. At the heart of the debate is a piece of land that both the Hindu and Muslim communities consider sacred. Controversy and violence have surrounded this site since at least 1853. Riots related to the disagreement resulted in over 2,000 deaths in 1992 and between 1,000 and 2,000 more deaths in 2002.[6] At the end of September, 2010 the Allahabad High Court was set to rule on the dispute to determine how the land would be distributed among the two communities.

[4] Information based on the company's website `http://www.reutersmarketlight.com/` (accessed June 29, 2012)

[5] See press release `http://www.reutersmarketlight.com/images/world-business-award-2010.pdf` (accessed June 29, 2012)

[6] For additional details on the history of the Ayodhya holy site dating back to 1528 see `http://www.bbc.co.uk/news/world-south-asia-11436552` (accessed June 29, 2012).

In anticipation of technology being used to spread rumors about the verdict and coordinate deadly riots, the Indian government banned bulk text messages beginning in the evening of September 22, 2010, up until the night of October 4, 2010. Messages in excess of 10 per day for an individual or 100 per day for a business are deemed to be bulk messages.

The verdict, delivered on September 30, 2010, ruled that the site be split into three parts, with two parts going to Hindus and one part to Muslims. In contrast to the expectations of the government, violent outbreaks and rioting were not observed or reported in the days following the announcement. During the ban RML continued collecting market information as usual. However, the ban made it impossible for RML to transmit this information to its subscribers.

4. Data and Variables

Our analysis makes use of two distinct databases, both provided by RML. The first database holds information about RML's subscribers. It includes a subscriber identification number, the start and end date of the subscription, the taluka, district and state the subscriber resides in and the subscriber's choices of up to three markets for each of two crops. The second database contains market information. For each crop this database contains the volume and high and low prices at any market trading the crop on any given day. We supplement the RML price and subscription data with a classification of the perishability of crops provided by an RML chief market reporter.

Other studies of geographic price dispersion (such as Jensen 2007, Aker 2008) have focused on situations where all markets under investigation were open every day (or every week). By contrast, in our case only a subset of all markets trading a specific crop is open on any given day. Further, one group of markets may be open on one day and another, possibly overlapping group of markets may be open on the next day. Moreover, since the trading of agricultural goods in India is heavily regulated by State Agriculture Marketing Boards which differ from state to state, it is more natural to compare geographic dispersions within state boundaries, where regulations and quality differences are arguably smaller than they are across state boundaries. This intra-state comparison also suffers less from fluctuations in weather patterns such the monsoon rains, which drive crop seasonality, and which enter and exit states at different times. We call the group of markets that are open within a state for a particular crop on a given day the crop-market-cluster for that crop-state-day. Our unit of analysis is the crop-market-cluster-day.

To investigate the impact of the RML information on geographic price dispersion we need to define and measure geographic price dispersion. The standard deviation σ_{ckt} of prices for a specific agricultural commodity c across all markets in market-cluster k trading on each day t is a natural measure of spatial price dispersion and is similar to measures widely used in the price dispersion literature (e.g. Brynjolfsson and Smith 2000, Sorensen 2000, Ghose and Yao 2011, Tang et al.

2010). We use the standard deviation of the price reported in all open markets for a specific crop within a state (i.e. a crop-market-cluster) as our measure of price dispersion. For robustness, we also examine price dispersion as measured by the range of prices, $(P_{\max} - P_{\min})$ where $P_{\max}$ and $P_{\min}$ refer to the maximum and minimum price across all markets selling crop c in market-cluster k on day t. This measure of price dispersion has also been used extensively in the literature (e.g. Abbott III 1992, Sorensen 2000, Ghose and Yao 2011). Throughout our analysis we use the high price of the day recorded in each of the markets to estimate the two price dispersion measures described above. For robustness, we also report results for the low price for both measures. We use superscripts H and L to index high and low prices.

Next we consider independent variables. The variable $perishability_c$ measures the extent to which crop c can be stored for future consumption. An agricultural expert and Chief Market Reporter at RML classified all crops as either high perishability (shelf life of less than four days), medium perishability (shelf life of between four days and two months), or low perishability (shelf life greater than two months). The variable $NumSubscribers_{ckt}$ is the sum of the total number of subscriptions that are active across all of the markets selling crop c in market-cluster k on day t. If a subscription is active for two (three) markets within a crop-market-cluster, then we count this as two (three) subscriptions.

For our study we utilize price data from August 22, 2010 to November 8, 2010 for a total of 257,907 individual crop-market-day observations. While our unit of analysis is the crop-market-cluster-day, we first need to address several issues with the unbalanced structure of the price data. First, note that we conduct our analysis utilizing data from a short time window around the period of the bulk text message ban. We do this for two reasons. Firstly, a short time horizon allows us to minimize the impact of seasonality on crop prices. Secondly, RML is constantly extending its portfolio of markets for which it offers the service. Over a longer time frame this would complicate our analysis as there would be new crop-market-clusters forming that did not previously exist. Stable crop-market-clusters are particularly helpful in accurately estimating the crop-market-cluster fixed effects. We verify that our results are not dependent on the time window we have chosen by also using longer and shorter time periods surrounding the ban.

Second, before constructing the crop-market-cluster panel and estimating price dispersion, we find it necessary to appropriately deflate prices. Food price inflation in India reached an annualized 18.3% at the end of December 2010 (The Economic Times 2011, Bartsch et al. 2010). Even in a fairly short time span, this rate of inflation can cause sharp increases in prices and corresponding increases in price dispersion. Failure to account for this will result in a linear increase in price dispersion with time. Rather than using the government-reported levels of inflation for each category of agricultural commodities – e.g. lentils, fruits or vegetables – we specify and estimate a model of the logarithm of price against a linear time trend for each crop with state-week fixed effects. This model estimates the inflation rate for different crops as well as helps capture factors that systematically impact all crops in a state over time, such as the progression of monsoon rains. Prices are then "discounted" to the beginning of the time window. Similar deflation procedures are frequently used in research on the price dispersion of agricultural goods in the developing world. For example, Jensen (2007) uses 2001 Rs. in his analysis of fisheries in India in the period 1997 to 2001.

Third, we find it necessary and reasonable to exclude some crop-market-days from our analysis as explained below: (1) We remove from our analysis Sundays and other major national holidays, such as Gandhi Jayanti (October 2, 2010) when almost no markets are open.[7] This removes 495 crop-market-days (0.2% of all crop-market-days). (2) One challenge of the crop-market-cluster day unit of analysis is that some markets rarely trade in a certain crop. These crop-markets can generate crop-market-clusters which appear in the data set infrequently. Removing such crop-markets results in fewer crop-market-clusters with more observations (i.e. days). For the main analysis we remove all crop-markets with fewer than ten crop-market-days in our study period, thus eliminating 3,264 crop-market-days (1.3% of all crop-market-days). For robustness, we perform our analysis without dropping any crop-markets and by changing the threshold of inclusion in the dataset from 10 to 20 and 30 days in a crop-market. (3) In order to measure geographic price dispersion on a given day it is necessary to have more than one open market. We remove 14,689 crop-market-days (5.7% of all crop-market-days) in states with only one market open for the crop and day.

By following the process described above we are left with 26,260 crop-market-cluster-day observations. Next we remove certain crop-market-cluster-day observations for the reasons described below: (1) Since we transform the standard deviation by taking its logarithm we exclude any observations with standard deviation equal to zero. The standard deviation of prices is zero when all prices within a crop-market-cluster are identical on any given day. Excluding these observations is considered best practice (Young and Young 1975). This excludes 597 observations (2.3% of all crop-market-cluster-days) from our sample. (2) We need at least two observations per crop-market-cluster in order to be able to estimate crop-market-cluster fixed effects. Therefore we eliminate all crop-market-clusters which have only a single observation, resulting in the removal of 5,736 observations (21.8% of all crop-market-cluster-days) from our sample. Note that removing these observations only changes the intercept in our fixed effects specification, which we discuss further in the next section, and has no impact on the magnitude or the significance of any of our independent variables of interest. (3) Even in the short time period we examine, new markets appear in our data

[7] Gandhi Jayanti marks the birth of Mohandas Gandhi, the "Father of the Nation" and is one of three official national holidays in India, as described in the Government of India's list of holidays: `http://india.gov.in/govt/pdf/govt_holiday_list_10.pdf` (accessed June 29, 2012).

Table 1 Summary of data at the crop-market day level.

	Bhindi - High Perishability			
	Mean	Stdev	Min	Max
High Price (Rs.)	1173.60	461.49	260.49	8556.79
Low Price (Rs.)	942.77	366.26	175.30	5659.70
Volume (Quintals)	38.49	56.85	1	900
	Onions - Medium Perishability			
	Mean	Stdev	Min	Max
High Price (Rs.)	1196.77	622.13	206.02	19002.97
Low Price (Rs.)	956.11	470.27	55.52	2414.94
Volume (Quintals)	950.78	3478.87	1	62000
	Bajra - Low Perishability			
	Mean	Stdev	Min	Max
High Price (Rs.)	1350.22	479.71	622.88	2505.26
Low Price (Rs.)	1325.71	492.37	77.41	2506.00
Volume (Quintals)	449.54	816.64	1	8000

Summary data for three crops with different levels of perishability at the crop-market-day level.

Table 2 Summary of data at the crop-market-cluster-day level.

	Perishability			
	High	Medium	Low	Total
Crop-market-clusters	643	469	559	1671
Crops	44	48	78	170
Observations	6273	4145	3931	14349

Summary data for different levels of perishability at the crop-market-cluster-day level.

set. This is due to RML adding crops in certain states and to the reopening of markets that were closed during non-harvest seasons for some crops. Any change in price dispersion for a crop within a crop-market-cluster is difficult to interpret when data is only available in the post-ban period. We keep only crop-states that have at least one crop-market-cluster day observation before, during and after the ban, therefore dropping 964 observations (3.7% of all crop-market-cluster-days). (4) Some crops (such as processed vegetables) are not traded in the APMC regulated markets. Instead, traders contact farmers directly to offer a farm gate price. In such cases, RML gathers price information by contacting traders in the area. Volumes for these crops are not collected, resulting in missing volume data. We drop 53 crops with more than 5% missing volume data (4,614 observations or 17.6% of all crop-market-cluster-days).

Table 1 presents summary data by crop-market-day for three crops of differing levels of perishability. Following the deflation and filtering of crop-market-day observations, we convert the data to the crop-market-cluster-day unit of analysis and further eliminate observations as described above, resulting in 14,349 observations. Note that by construction on any given day, only one crop-market-cluster is open in each state. A summary of the crop-market-cluster-day data is given in Table 2.

5. Identifying the Main Effect

The bulk text message ban, which was completely unanticipated by RML and all other market participants, provides a natural experiment that alleviates potential concerns of endogeneity. Note that all other sources of information retrieval, such as physically visiting or calling markets, family and friends, were still viable options for farmers throughout the text message ban. This allows us to test whether the loss of RML price information had a measurable impact on price dispersion across the markets in which RML is offered over and above the impact of access to ICT infrastructure. To do so we examine whether price dispersion is different before, during and after the bulk text message ban. Specifically, we estimate an econometric model of the form:

$$\log(\sigma_{ckt}) = \alpha_{ck} + \beta_1 DuringBan_t + \beta_2 PostBan_t + \delta_t + \epsilon_{ckt} \quad (1)$$

where σ_{ckt} is the price dispersion of crop c measured as the standard deviation of high prices recorded across market-cluster k on date t. $DuringBan_t$ is a dummy variable taking the value of 1 when the bulk text message ban is in effect and zero otherwise. $PostBan_t$ is a dummy variable taking the value of 1 after the bulk text message ban has been lifted and zero otherwise. By using the logarithm of the standard deviation of prices we can better control for any differences in levels between crops, states or specific markets that remain constant through time with fixed effects α_{ck}, which we discuss below. We also control for day-of-week fixed effects with the vector of controls δ_t, which we also discuss below.

Of course, the set of markets that are open for a crop on any given day would systematically influence the price dispersion observed on that day. For example, crop-market-cluster A could be three APMC-regulated auction markets that are all very close to each other and have similar volumes. Crop-market-cluster B could be four APMC-regulated auction markets and a domestic terminal market that are far apart and exhibit very different volumes. We expect price dispersion to differ systematically in these two crop-market-clusters. To control for the time-invariant characteristics of each crop-market-cluster, and for the average effect of time-variant characteristics, we include a crop-market-cluster fixed effect α_{ck} corresponding to each market cluster k for each crop c in our econometric specification. More specifically, the crop-market-cluster fixed effect, which is an important element of our identification strategy, will capture and control for any differences in natural price dispersion between crops or any other crop-specific differences, such as perishability (i.e. the crop-market-cluster fixed effect subsumes the crop fixed effect), differences in the number of markets and composition of markets in terms of terminal or auction markets within a cluster, differences in the transportation costs between markets within a cluster, differences in population, market or farmer density, as well as differences in local preferences, tastes or practices. Furthermore, since market clusters are defined within state boundaries, the crop-market-cluster fixed effects will partially control for the different stages of the season that a crop is in across states.

We also include a vector of day-of-week dummy variables δ_t to control for any systematic differences across different weekdays. Ideally we would have liked to include date fixed effects to control for any unobserved temporal heterogeneity that impacts all crops and markets. However, such fixed effects cannot be included in our specification because they are perfectly collinear with the text message ban dummy variable used for identification of the main effect.

While the crop-market-cluster fixed effects control for time-invariant sources of heterogeneity (and the average effect of time-variant sources of heterogeneity) across crop-market-clusters, they do not control for differences in the error structure across crop-market-clusters. Ignoring either heteroskedasticity or correlation in the errors will result in unreliable estimation of standard errors and erroneous inference (Gerardi and Shapiro 2009). Indeed, our specification results in errors which are both heteroskedastic and serially correlated.[8] Fortunately, with 170 crops and 64 days in our analysis, we can estimate fairly flexible error structures to reduce concerns that the errors we use to assess statistical significance are underestimated.

To this end, we first cluster errors at the crop level to allow for arbitrary correlation of errors within a crop as well as correlation of errors across crops on a given day, and for error variances that can differ by crop and day. This is a more flexible error structure than clustering at the crop-market-cluster level as it allows different crop-market-clusters within a crop to have correlated errors (Moulton 1986, Angrist and Pischke 2008). In our context this is especially important as two crop-market-clusters may be composed of many of the same markets.

The text message ban, in addition to having an impact on the *average* price dispersion, may also have changed the variance-covariance matrix of the residuals – i.e. the error structure during the ban may be different to that before or after the ban. Failure to account for this change in the error structure during the ban could again result in unreliable standard errors and erroneous inference. Clustering on the crop level alone, as discussed above, fails to account for this as it assumes that the error structure remains unchanged during the ban. A potential option that allows for the error variances in the pre, during and post ban periods to be different is to cluster the errors on the "ban stage," in addition to clustering on to the crop level (Cameron et al. 2011). However, when errors are clustered on more than one dimension, inference based on asymptotic analysis is reliable only as the *smallest* number of cluster groups tends to infinity. Clustering errors on the pre, during and post ban periods would result in only three cluster groups, well below the threshold of around 40 or 50 cluster groups suggested by previous research (Wooldridge 2003, 2006). As an alternative, we choose to cluster the errors on the date in addition to clustering on the crop level. This allows for errors associated with observations in different crop-market-clusters to be correlated within

[8] To verify that error variances are not homoskedastic, we perform a Wald test for heteroskedasticity of the residual variance across crop-market-clusters. Under the null hypothesis of a common error variance, the test statistic follows a χ^2 distribution (see Baum 2001, Greene 2002, p. 323-324). We reject the null hypothesis of homoskedastic error variance ($\chi^2(1671) = 5.7 \times 10^{34}; p < 0.0001$) indicating that error variances across crop-market-clusters are not identical. We test for serial correlation by performing an F-test. Under the null hypothesis of no first order autocorrelation, the test statistic follows an F distribution. (see Drukker 2003, Wooldridge 2002, p. 274-276). We reject the null hypothesis of no first order autocorrelation ($F(1, 382) = 26.61; p < 0.0001$).

Table 3 Main effect regression results.

VARIABLES	$\log(\sigma^H)$
DuringBan	0.052**
	(0.026)
PostBan	0.017
	(0.035)
Observations	14,349
Day of Week FEs	YES
Adjusted R-Squared	0.864
Min. No. obs per crop-market	10
Min. No. obs per cluster	2
Start Date	23-Aug-10
End Date	8-Nov-10
Crop-market-clusters	1671

Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** p<0.01, ** p<0.05, * p<0.1

Table 4 Number of subscriber regression results.

VARIABLES	$\log(\sigma^H)$
DuringBan_VeryLow	0.049
	(0.042)
DuringBan_Low	0.028
	(0.051)
DuringBan_Medium	-0.014
	(0.072)
DuringBan_High	0.083**
	(0.042)
DuringBan_VeryHigh	0.072*
	(0.037)
PostBan	0.017
	(0.035)
Observations	14,349
Day of Week FEs	YES
Adjusted R-Squared	0.864
Min. No. obs per crop-market	10
Min. No. obs per cluster	2
Start Date	23-Aug-10
End Date	8-Nov-10
Crop-market-clusters	1671

Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** p<0.01, ** p<0.05, * p<0.1

a day but uncorrelated across different dates. As we have 64 dates in our panel this provides a large enough number of cluster groups for errors to be reliably estimated while still allowing for changes to the variance covariance matrix that are date specific. In summary, we cluster errors in two dimensions: on the crop level and the date level.

5.1. Main Result

The results of the regression for Model (1) are presented in Table 3. The coefficient on *DuringBan* is positive and significant (p-value 4.5%), indicating that price dispersion was indeed higher during the text message ban. Furthermore, price dispersion increases occurred only during the ban, when RML information was not available to market participants, as evidenced by an insignificant coefficient on *PostBan* (p-value 63.1%). Since the dependent variable is the logarithm of the standard deviation, the interpretation of the *DuringBan* and *PostBan* coefficients is the percentage change in price dispersion during these periods. There was a 5.2% increase in price dispersion during the text message ban. Because other ways of obtaining price information were unaffected by the ban, this increase in price dispersion can be attributed to the loss of RML price information alone. Previous research has shown that the introduction of mobile phones in developing countries can reduce price dispersion by 10–20% (Aker 2008, 2010), suggesting that access to timely and accurate information can contribute an additional 25–50% of the improvement seen through access to mobile phones alone.

5.2. Number of RML Subscribers

To determine whether the increase in price dispersion during the ban is indeed linked to the cessation of the information provided by RML, we investigate whether the impact of the ban is greater in areas where there are a relatively large number of RML subscribers as opposed to areas where there are fewer subscribers. To do this, we use the $NumSubscribers$ variable, which denotes the number of subscribers that receive information for each of the markets in a crop-market-cluster. Since there is little temporal variability in $NumSubscribers$ during our study period, we average $NumSubscribers$ over time. Finally, we calculate a within-crop percentile score for the average of $NumSubscribers$ for each crop-market-cluster. We segment crop-market-clusters in the lowest 40% into one group and separate the remaining 60% into four groups of 15% each. Dummy variables for each group are then interacted with the $DuringBan$ variable for identification using the following specification:

$$\log(\sigma_{ckt}) = \alpha_{ck} + \beta_1 DuringBan_t \times NumSubscribersGroup_{ck} + \beta_2 PostBan_t + \delta_t + \epsilon_{ckt} \qquad (2)$$

where $NumSubscribersGroup$ is a set of dummy variables taking the value of 1 when the average number of subscribers for crop c in market-cluster k is in that group, corresponding to a percentile range within a crop, and all other variables are as described previously.

The results of the regressions for Model (2) are listed in Table 4. The significant coefficients on the two groups corresponding to the high and very high percentiles of subscribers, 70–85 and 85–100 percentiles, confirm that RML is the most likely cause of the observed reduction in price dispersion. Importantly, price dispersion is not significantly higher during the ban than pre or post ban in market clusters for which there are relatively low numbers of subscribers within a crop.

5.3. Alternative Explanations

Although we have shown that price dispersion increase during the ban was greatest in areas where RML has the largest number of subscribers, there are a number of potential alternative explanations that we must rule out before we can confidently conclude that RML is causing a reduction in price dispersion. One possible alternative explanation is that, as the Indian government expected, there was civil unrest at the time of the text message ban. This would be correlated with the ban dummy and could potentially be correlated with prices if market participants changed their behavior due to the civil unrest. For example, if there was significant civil unrest farmers may have felt too unsafe to harvest their crops and visit the local mandis to sell them, and similarly traders may have been scared to go to the market to buy goods. In this case, supply and demand would be thin and price

Table 5 **Time, volume and price regression results.**

VARIABLES	(1) $\log(Volume)$	(2) $\log(P^H)$	(3) $\log(\sigma^H)$	(4) $\log(\sigma^H)$
DuringBan	0.001	0.013	0.052**	0.053**
	(0.025)	(0.009)	(0.025)	(0.027)
PostBan	0.051*	-0.018**	0.019	0.022
	(0.030)	(0.008)	(0.032)	(0.035)
Observations	14,349	14,349	17,015	11,624
Day of Week FEs	YES	YES	YES	YES
Adjusted R-Squared	0.939	0.990	0.859	0.864
Min. No. obs per crop-market	10	10	10	10
Min. No. obs per cluster	2	2	2	2
Start Date	23-Aug-10	23-Aug-10	16-Aug-10	1-Sep-10
End Date	8-Nov-10	8-Nov-10	15-Nov-10	30-Oct-10
Crop-market-clusters	1671	1671	1892	1461

Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** p<0.01, ** p<0.05, * p<0.1

dispersion might increase irrespective of the availability of information. We do not believe this is the case for three reasons.

First, one of the authors was working on the project in India at the time of the bulk text message ban. While civil unrest was expected on the days surrounding the Ayodhya verdict, none was reported on the news, heard of, or personally observed.[9] Second, even if civil unrest was a legitimate concern we should be able to identify this in the data through a significant decrease in transacted volumes during the ban. The results of the regression in Column 1 of Table 5 show that volumes were not significantly different during the ban as compared to pre-ban. *PostBan* volumes were marginally higher which may be due to the November 5, 2010 Diwali festivities.

Third, if there were any tensions these would be between the majority Hindu and the minority Muslim population. We would therefore expect to see a more significant disruption in states with a relatively high Muslim population as opposed to states with almost no Muslim population. We verify that this is not the case by comparing the change in price dispersion during the ban in areas with a high vs. low percentage of Muslims in the population. Using data from the 2001 Census of India, which details state-level populations by religious affiliation, we classify each of the 13 states as above or below the national median Muslim population as a percentage of total population in the state.[10]As we report in Table 6, the increase in price dispersion during the ban occurs equally in crop-market-clusters belonging to states with high as well as low (relative) muslim populations

[9] See `http://www.guardian.co.uk/commentisfree/belief/2010/sep/30/politics-not-faith-brings-violence` and `http://www.ndtv.com/article/india/ayodhya-verdict-temple-politics-in-uttar-pradesh-56379` (accessed June 29, 2012) for examples of news media highlighting the lack of violence following the verdict.

[10] `http://www.censusindia.gov.in/Census_Data_2001/Census_data_finder/C_Series/Population_by_religious_communities.htm` (accessed June 29, 2012)

Table 6 Muslim population and price dispersion.

VARIABLES	(1) $\log(\sigma^H)$
During Ban x High Muslim x High Num Subscribers	0.067*
	(0.035)
During Ban x Low Muslim x High Num Subscribers	0.095*
	(0.050)
During Ban x High Muslim x Low Num Subscribers	0.009
	(0.035)
During Ban x Low Muslim x Low Num Subscribers	0.081
	(0.054)
PostBan	0.017
	(0.035)
Observations	14,349
Day of Week FEs	YES
Adjusted R-Squared	0.864
Min. No. obs per crop-market	10
Min. No. obs per cluster	2
Start Date	23-Aug-10
End Date	8-Nov-10
Crop-market-clusters	1671

Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** p<0.01, ** p<0.05, * p<0.1

where RML has a high number of subscribers (above the 70th percentile within a crop). Conversely, the price dispersion does not change during the ban in crop-market-clusters with a low number of subscribers (below the 70th percentile within a crop), irrespective of the state's muslim population. Therefore, one can conclude that the number of subscribers and not the religious makeup of a state was the driver of the change in price dispersion during the ban.

A second alternative explanation is that traders colluded to offer low prices during the ban when farmers did not have the price information. If traders colluded in some markets and not in others, or if the extent to which farmers were able to collude differs across markets, then prices in some markets would drop more than in others and we would observe an increase in price dispersion. Column 2 of Table 5 shows that prices were on average unchanged during the text message ban.

5.4. Additional Robustness Checks

The text message ban provides us with a natural experiment leaving little concern for endogeneity in our analysis. However, random fluctuations in price dispersion may coincide with the timing of the ban. To ensure our results are not the consequence of a spurious correlation, we perform several robustness checks. First, we confirm that the results are not sensitive to the time window for which we have run the regressions. Columns 3 and 4 of Table 5 show the results of regressions for time periods covering August 15, 2010 to November 15, 2010 (an additional week both before and after

Table 7 Main effect regression results with price dispersion measure robustness.

VARIABLES	(1) $\log(P^H_{\max} - P^H_{\min})$	(2) $\log(\sigma^L)$	(3) $\log(P^L_{\max} - P^L_{\min})$
DuringBan	0.045*	0.062**	0.077***
	(0.026)	(0.030)	(0.026)
PostBan	0.013	0.017	0.021
	(0.035)	(0.037)	(0.037)
Observations	14,349	14,245	14,244
Day of Week FEs	YES	YES	YES
Adjusted R-Squared	0.874	0.838	0.877
Min. No. obs per crop-market	10	10	10
Min. No. obs per cluster	2	2	2
Start Date	23-Aug-10	23-Aug-10	23-Aug-10
End Date	8-Nov-10	8-Nov-10	8-Nov-10
Crop-market-clusters	1671	1670	1670

Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** p<0.01, ** p<0.05, * p<0.1

the ban) and September 1, 2010 to October 31, 2010 (approximately one week less both before and after the ban), respectively. The coefficients on the *DuringBan* dummy variable are largely unchanged, with the longer and shorter time windows showing that our results are not dependent on the time frame chosen.

Next, we verify that the results are not sensitive to the measure of price dispersion by using the log of the range of prices instead. The price range is the difference between the maximum and the minimum price observed across all markets in a state. We also examine whether price dispersion for the low price recorded in each market is higher during the ban. Results from the regressions are shown in Table 7. The coefficient of the *DuringBan* is positive and statistically significant in all specifications.

To rule out the possibility that our results are driven by our choice of sample or any of the filters we apply to the data in constructing the panel, we conduct several robustness checks. First, we examine whether our results are dependent on the number of observations required for a crop-market to be included in the panel. Table 8 shows the results of regressions with different cutoffs for the minimum number of observations needed to include a crop-market in the data set. The results are robust to including crop-markets with at least one (Column 1), 20 (Column 2) or 30 (Column 3) observations. We also examine the sensitivity of our results to the number of observations in a crop-market-cluster in two ways. First, we run a regression including only crop-market-clusters which have observations before, during and after the ban. Column 4 of Table 8 shows that the results are largely unchanged. Second, we determine whether the choice to include crop-market-clusters with more than one observation is driving our results. Column 5 of Table 8 shows that the results are robust to using only crop-market-clusters with at least 10 observations. Overall our robustness

Table 8 **Main effect regression results with robustness to the number of days that a market must be open in the dataset to be included in the regressions.**

VARIABLES	(1) $\log(\sigma^H)$	(2) $\log(\sigma^H)$	(3) $\log(\sigma^H)$	(4) $\log(\sigma^H)$	(5) $\log(\sigma^H)$
DuringBan	0.052**	0.048*	0.049*	0.050*	0.051*
	(0.026)	(0.026)	(0.025)	(0.029)	(0.030)
PostBan	0.015	0.016	0.011	0.028	0.024
	(0.035)	(0.034)	(0.034)	(0.038)	(0.039)
Observations	14,017	14,751	15,150	9,789	9,417
Day of Week FEs	YES	YES	YES	YES	YES
Adjusted R-Squared	0.864	0.858	0.851	0.858	0.866
Min. No. obs per crop-market	1	20	30	10	10
Min. No. obs per cluster	2	2	2	2	10
Start Date	23-Aug-10	23-Aug-10	23-Aug-10	23-Aug-10	23-Aug-10
End Date	8-Nov-10	8-Nov-10	8-Nov-10	8-Nov-10	8-Nov-10
Crop-market-clusters	1689	1579	1467	539	379

Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

checks confirm that the price information provided by RML has a statistically significant impact on the geographic price dispersion of agricultural crops in India.

6. Information, Perishability and Market-to-Market Distances

While we have established that the information provided by RML reduces geographic price dispersion on average, in this section we begin by examining whether this effect is observed equally for all crops independent of perishability. We follow this with a discussion of the differences between market-to-market distances for crop-market-clusters with high and low number of subscribers.

6.1. Perishability

Perishable crops tend to command higher profit margins, but are also considered more risky (Joshi et al. 2006). If the availability of timely and accurate information substantially reduces the risk associated with perishables, services such as RML should allow farmers to increase production of high-value crops. Identifying which types of crops benefit the most from improved information flows should help farmers decide how to spend money on improving information flows, and enable information providers such as RML, as well as international aid organizations, to better decide which crops to focus their efforts on. Despite the practical importance of investigating how perishability moderates the relationship between information flows and geographic price dispersion, difficulties in collecting data and exogeneity concerns have limited previous research to focus on one or at best two agricultural commodities in a limited number of markets (Aker and Fafchamps 2010). And even then, the crops examined were chosen to differ in terms of perishability but otherwise be as homogeneous as possible to reduce concerns regarding correlated omitted variable bias. The richness of our dataset allows us to circumvent these difficulties and investigate this question more thoroughly.

Access to timely and accurate information may be less critical for low perishability crops, which can be stored for a relatively long time, and transported further away and to multiple markets at a relatively low cost and without spoiling. Perishable crops, on the other hand, need to be sold in a relatively short time window. Given the cost and lack of suitable infrastructure, such as cold storage trucks and cold storage facilities, they cannot be easily transported to more than one market, or stored. Therefore having access to timely and accurate information is more critical for perishables. We expect the impact of information on price dispersion to be greater for perishable crops than for non-perishable crops.

To examine how perishability moderates the value of timely and accurate information, we examine how the ban impacts price dispersion for crops of varying perishability. We identify the impact of different levels of perishability by interacting the perishability variable with the $DuringBan_t$ variable. We therefore estimate

$$\log(\sigma_{ckt}) = \alpha_{ck} + \beta_1 DuringBan_t \times Perishability_c + \beta_3 PostBan_t + \delta_t + \epsilon_{ckt} \tag{3}$$

where $Perishability$ is a set of dummy variables indicating the level of perishability for a crop as high, medium and low perishability, and all other variables are as described in Model (1). Note that we do not need to include the $Perishability$ dummy variables directly in the model as the perishability level for a crop is captured completely by the crop-market-cluster fixed effect. Since perishability levels are mutually exclusive dummy variables their coefficients should be interpreted as the change in price dispersion relative to the same level of perishability before the ban. Note that it is neither necessary nor useful to interact the number of RML subscribers with the perishability variables: The $NumSubscriberGroup$ variable is calculated within each crop and therefore $Perishability$ and $NumSubscriberGroup$ are orthogonal by construction. Further, it would result in a loss of power as more interaction terms would need to be added to the model.

The results of Model (3) presented in Column 1 of Table 9 demonstrate that providing price information via a reliable and independent third party is more beneficial in terms of reducing geographic price dispersion for crops of high and medium levels of perishability. Crops with low levels of perishability do not benefit from the information in a statistically significant manner. Interestingly, using a similar model to equation (3) but using volume as the dependent variable, which we report in Column 2 of Table 9, we find that volumes during the ban did not change in any statistically significant manner for any level of perishability. This suggests that the information provided by RML (over and above the information farmers can get through other means) is not a critical driver in better matching demand and supply for crops of low perishability.

Table 9 Perishability regression results.

VARIABLES	(1) $\log(\sigma^H)$	(2) $\log(Volume)$
DuringBan_HighPerish	0.075*	0.006
	(0.038)	(0.026)
DuringBan_MediumPerish	0.116***	0.001
	(0.037)	(0.039)
DuringBan_LowPerish	-0.051	-0.007
	(0.034)	(0.049)
PostBan	0.017	0.051*
	(0.035)	(0.030)
Observations	14,349	14,349
Day of Week FEs	YES	YES
Adjusted R-Squared	0.864	0.939
Min. No. obs per crop-market	10	10
Min. No. obs per cluster	2	2
Start Date	23-Aug-10	23-Aug-10
End Date	8-Nov-10	8-Nov-10
Crop-market-clusters	1671	1671

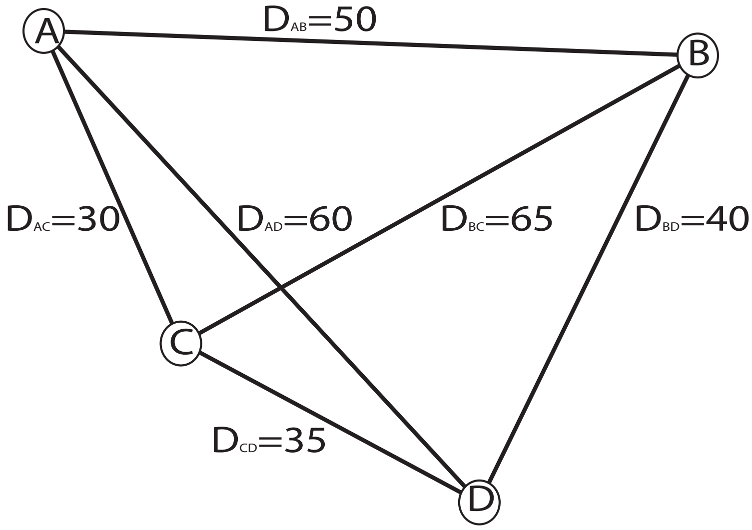
Crop-market-cluster-day panel regressions with two-way error clustering: at the crop level and at the day level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.2. Market-to-market distances

In this section we examine whether crop-market-clusters with high and low numbers of subscribers differ systematically from one another. If there are systematic differences, then it is possible that only clusters with certain characteristics will achieve the penetration levels necessary to affect price dispersion. On the other hand, if crop-market-clusters with low numbers of subscribers have similar characteristics to those with high numbers of subscribers, then we would expect RML subscription in these low usage clusters to increase with time, and eventually result in lower price dispersion.

One important dimension in which market-clusters differ is the distribution of market-to-market distances within a cluster. To examine this, we used geolocation data for each of the 1,376 markets that we collected using Amazon Mechanical Turk to construct different metrics of market-to-market distances within a crop-market-cluster. Amazon Mechanical Turk is a micro-outsourcing service that allows users to pay individuals around the world to answer short, repetitive questions. We provided input data on the state and taluka name of each market to individuals accepting work through Amazon Mechanical Turk based in India. We instructed them to use online geolocation tools such as Google Earth to find and report the longitude and latitude of the location of the market. The input data on each market was sent to two distinct individuals. If the locations provided were within 10 miles of each other, we took the average as the market location. Where the responses differed by more than this threshold, we re-submitted the input data for the location to two new individuals. If we did not get consensus between these two individuals, or if a location

Figure 1 **Example of distance measures for a crop-market-cluster.**



could not be identified at all, one of the authors or a research assistant found the location using a combination of online search and consulting physical maps at the British library.

We devise several measures of the distribution of market-to-market distances within a crop-market-cluster to examine statistically, as well as visually, whether high and low subscriber crop-market-clusters are systematically different from one another in this dimension. Throughout we denote the direct route distance between markets i and j as $D_{ij} = D_{ji}$. For example, the distance between markets A and B in the hypothetical crop-market-cluster shown in Figure 1 is 50 miles (all distances are measured in miles). Our first measure is $NearestMarketDistance$, the distance between a market and its nearest neighboring market in the crop-market-cluster. For the example in Figure 1, $NearestMarketDistance_A = \min(D_{AB}, D_{AC}, D_{AD}) = \min(50, 30, 60) = 30$. Similar analysis for markets B, C and D results in a $NearestMarketDistance$ distribution of $\{30, 40, 30, 35\}$ for this crop-market-cluster. Our second distance measure, $MarketDistance$, utilizes all of the market-to-market distances, not just the nearest market distance. In Figure 1, this corresponds to a distribution $\{D_{AB}, D_{AC}, D_{AD}, D_{BC}, D_{BD}, D_{CD}\}$ or $\{50, 30, 60, 65, 40, 35\}$. We calculate the mean, median and standard deviation of the distribution of both distance measures for each crop-market-cluster, resulting in $AverageNearestMarketDistance = 33.75$, $MedianNearestMarketDistance = 32.5$, $StandardDeviationNearestMarketDistance = 4.79$, $AverageMarketDistance = 46.67$, $MedianMarketDistance = 45$ and $StandardDeviationMarketDistance = 12.02$ in our example.

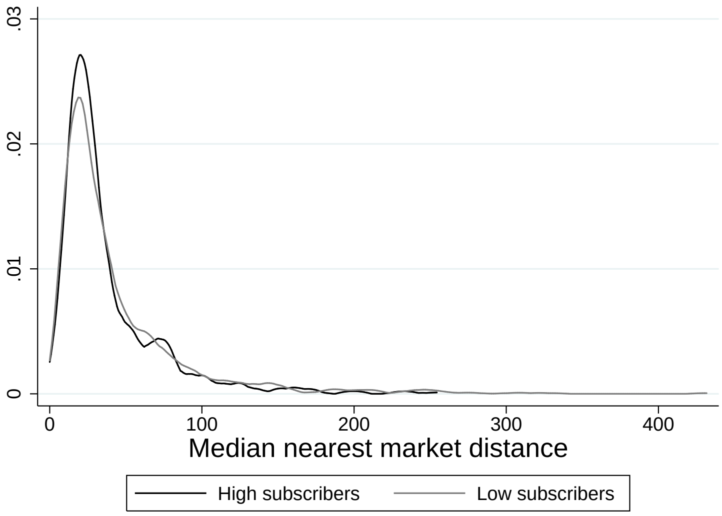
To statistically examine differences in the distribution of distance measures, we perform Kolmogorov-Smirnov tests of the equality of distributions of each distance metric across high and low number of subscriber crop-market-clusters. For the analysis we define high number of subscriber crop-market-clusters as those above the 70th percentile within a crop, corresponding to the crop-market-clusters for which we identified a significant increase in price dispersion during the

Table 10 Differences in high and low number of customer crop-market-clusters.

	Kolmogorov-Smirnov
Average Nearest Market Distance	0.336
Median Nearest Market Distance	0.034
St.Dev. Nearest Market Distance	0.001
Average Market Distance	0.003
Median Market Distance	0.054
St.Dev. Market Distance	0.048

P-values for Kolmogorov-Smirnov tests for equality of distribution functions between high and low number of subscriber crop-market-clusters using crop-market-cluster distance metrics.

Figure 2 Distribution of market-to-market distances.



Note. Distribution of median nearest market distance for high and low number of subscriber crop-market-clusters.

ban. Low number of subscriber crop-market-clusters are those below the 70th percentile within a crop. The results of the tests, summarized by the p-values in Table 10, show significant differences in the distributions of market-to-market distance metrics between high and low number of subscriber crop-market-clusters. Figure 2 shows the kernel density distribution of the median of $NearestMarketDistance$ for high and low number of subscriber crop-market-clusters providing further insight into the difference between high and low number of subscriber crop-market-clusters. From the figure it is evident that there are no crop-market-clusters with a high number of subscribers and median nearest market distances over 300 miles. However, crop-market-clusters with a low number of subscribers have, in some cases, a median distance greater than 400 miles. These differences suggest that to a large extent high and low number of subscriber crop-market-clusters are not comparable in terms of inter-market distances. We therefore expect that only crop-market-clusters which have market-to-market distance distributions similar to those observed in crop-market-clusters with a high number of subscribers will attain the necessary number of subscribers to benefit from RML price information.

To identify which low subscriber crop-market-clusters could potentially become high subscriber crop-market-clusters we match the market-to-market distribution using the six measures described above. We first calculate the 10th and 90th percentile of each of the distance measures using only the high subscriber crop-market-clusters. We then identify the low subscriber crop-market-clusters which have distance measures within this 10th and 90th percentile range on all of the distance measures. Out of the 1,070 low subscriber crop-market-clusters we identify 476 (44.5%) crop-market-clusters that fit these criteria. This is encouraging as it suggests that while there are some crop-market-clusters which may never attain the necessary level of customers to impact geographic price dispersion, not all low subscriber crop-market-clusters differ from high subscriber crop-market-clusters. Nearly 45% of current low subscriber crop-market-clusters are sufficiently similar to the high subscriber crop-market-clusters in terms of market proximity that given enough time they could gain a sufficient number of customers to reduce geographic price dispersion.

7. Conclusions

New ICTs such as mobile phone networks are rapidly changing supply chains in developing economies by reducing the cost of acquiring and transmitting information. Previous research has verified that access to this new technology enables farmers to strategically choose markets in which to sell their produce, correcting demand-supply mismatches and reducing geographic price dispersion. This paper contributes to the literature on the effect of information and communication technologies on prices in rural agriculture markets by examining how the provision of regular, timely and accurate price information delivered via existing ICT impacts geographic price dispersion. Utilizing a detailed dataset from RML, we exploit a natural experiment, in which bulk text messages were banned unexpectedly for 12 days across India. Our results show that the average spatial price dispersion of 170 crops across 13 states increased by 5.2% (std. error 2.6%, p-value 4.5%) during the ban as compared to the period before the ban. When the ban was lifted, price dispersion returned to pre-ban levels.

The natural experiment identification strategy removes any endogeneity concerns as it is uncorrelated with any decisions made by farmers or by RML management. We show that our results are robust to the choice of dispersion measure. We also explore several alternative explanations, as well as potential issues of misspecifcation and spurious correlation, but find no evidence that casts doubt on the causal nature of our results. Furthermore, with 170 crops and 64 days in our analysis, we can estimate fairly flexible error structures, resulting in error variances that can differ by crop and day. We allow for arbitrary correlation of errors within a crop, as well as correlation of errors across crops on a given day. This reduces any concerns that the errors we use to assess statistical significance are underestimated.

Importantly, the highest price dispersion during the ban is recorded in areas where RML has the largest number of subscribers. It appears that there is a threshold number of customers, which may vary by crop, above which provision of regular, timely and accurate price information can significantly influence geographic price dispersion. Since we do not have information on the number of farmers by crop-state, we are not able to identify the precise penetration level needed for RML to have a measurable impact on price dispersion. However, RML executives we have spoken with estimate the penetration of this service to be as low as 2% percent in most markets, suggesting that the RML information service has an effect even at low levels of penetration.[11]

In addition, we explore the linkages between price dispersion and perishability. We find that crops with a high or intermediate perishability level exhibit lower price dispersion when price information is available via RML. Low perishability crops do not benefit from the information service. It is possible that access to mobile phones has already made the markets for these crops fairly efficient or that information is not the barrier to market efficiency, rather reliable infrastructure for transporting these typically heavy crops. Future research should attempt to disentangle the two effects.

Our results have important managerial and policy implications. On the managerial side, they provide support for the business model of third party information providers, such as RML, by showing that these services make a significant difference in the functioning of agricultural crop markets in the developing world. Further, firms offering such price information services should focus their operational and marketing efforts on crops with high and medium levels of perishability and on market-clusters that are sufficiently similar to those market-clusters with a high number of subscribers in terms of the inter-market distance composition.

Policy makers and international aid organizations should take our results into consideration when deciding how to allocate funds aimed at improving welfare in developing countries. Purchasing subscriptions to a price information service, such as RML, on behalf of farmers or providing support to companies offering such a service could be a low-cost option for reducing market inefficiencies. As farmers tend to share information, for-profit companies may under-provide these types of information services because they cannot reap the full benefit of doing so. Perhaps subsidies to such information providers are therefore warranted. Ayres and Levitt (1998) reach a similar conclusion when examining the impact of Lo-jack, an unobservable automobile security device, on crime rates.

[11] True penetration is likely to be much higher than the number of subscribers may suggest as subscribers apparently share their RML information with a number of family members and colleagues. See `http://www.reutersmarketlight.com/` (accessed June 29, 2012).

The significant positive externalities of installing Lo-jack in a single car far outweigh the benefit to the individual and subsidizing the service would improve social welfare.

Our results are not limited to the agriculture market setting investigated here, but can be extended to any developing economy supply chain where technological coordination and information dissemination can be achieved via mobile phones. Future research may identify areas where existing technological infrastructure can be leveraged to improve market efficiency. Researchers in information systems and operations management should embrace the natural experiment econometric methodology whenever possible to investigate these issues.

Although our rich data set and the natural experiment specification have allowed for a robust investigation of the value of timely and accurate information, there are still a number of limitations and areas for future research. First, while we do show that crop-market-clusters with a relatively small number of subscribers are not affected by RML price information, we only observe prices in markets in which RML sources information. A difference in differences approach would allow us to examine whether prices in markets that are completely unserved by RML exhibited higher levels of price dispersion during the ban, further dispelling any concerns about seasonality or alternative explanations. Second, the bulk text message ban was limited in length. This limits the statistical power to examine price dispersion changes. It also limits the ability to measure RML's impact on temporal price dispersion. On the other hand, the short duration of the ban had the benefit of not giving farmers sufficient time to respond by adjusting their behavior, which might have occurred if the disruption had lasted longer. Finally, previous studies have been able to examine the distance between markets by examining how the distance between market pairs impacts price dispersion when mobile phones are introduced. Performing our analysis at the crop-market-cluster level complicates any investigation of the role that market-to-market and customer-to-market distances play in the impact of ICT-enabled price information on price dispersion, due to the multitude of ways in which these distances can be calculated for a crop-market-cluster. Future research can address this through an alternative econometric specification.

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