Essays on the Effect of Technological Innovation on Markets in Developed and Developing Economies

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DECLARATION

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London Business School is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

To Christy, for teaching me what life is all about.

"The length of this document defends it well against the risk of its being read."
Sir Winston Churchill

ABSTRACT

This thesis is an empirical investigation into the impact technology has on markets in both developing and developed economies. I first examine how a text message based service providing price information to market participants is affecting geographic price dispersion in India's agriculture markets over and above mere access to mobile phones. Exploiting a natural experiment where bulk text messages were unexpectedly banned across India for twelve days, I observe a statistically and economically significant 7.6% increase in price dispersion attributable to the loss of the information provided through the service. Increases are concentrated in crops with high and medium levels of perishability. The research provides evidence that fair and unbiased information can be beneficial in creating more efficient agriculture markets.

Next I describe the technology involved in collecting and disseminating the price information, highlighting the difficulties involved with setting up a successful and impactful information system where low-tech solutions are the primary price discovery method, and the way in which these challenges were overcome.

Transitioning into developed economies, I examine brokers' routing practices to two competing electronic exchanges. Using data from U.S. brokerage firms, I find that affiliation, not network effects, is the most important factor driving the percent of orders sent to an exchange. The results highlight the importance of factors beyond traditional network effects in explaining new market success/failure and the need for exchanges to retain a group of dedicated users.

Finally I examine technology-enabled trading practices that may negatively impact markets resulting in "flash crashes." Using a simulated equity market, I contrast current trading rules to a proposed rule in terms of market quality and high frequency trader profitability during times of high volatility. High frequency trading can lead to market aberrations highlighting the importance of creating policies that ensure market quality and prevent future flash crashes.

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CHAPTER 1

INTRODUCTION

Understanding how technology impact the way in which people interact in markets and how managers run businesses is a fertile research area with significant practical applications. The reach of the research spreads to developing economies where non-governmental organizations (NGOs) and international organizations such as the World Bank and the International Monetary Fund regularly fund initiatives with the goal of combating poverty. However, with limited budgets not all initiatives can be funded and strategic decisions must be made. In developed economies, investors spend millions of dollars introducing new electronic markets, only to later shut down due to a lack of use.

Understanding where the marginal benefits of technology are largest, especially in light of budget constraints, can help in the allocation of resources in both developed and developing economies. In order to achieve this, we must be able to accurately measure and predict how funding initiatives and changes to market policies will impact the overall economy. My thesis aims to identify areas in which technology benefits society, as well as to make policy suggestions to mitigate any detrimental effects. The hope is that this research, and the research the follows from it, will enable policy makers to choose the best strategies for making markets and operations more efficient worldwide.

Before entering the research chapters of my thesis, I find it is useful for the reader to have some background on the related academic literature. We therefore spend some time in Chapter 2 reviewing literature relevant to each of the four research chapters. The chapter is by no means meant to be an exhaustive survey of the literature but serves as a good base for the discussion that occurs in subsequent chapters.

The first two research chapters discuss informationa technology (IT) use for price dissemination in developing economies. Chapter 3, *Is IT Access Enough? Evidence from a Natural Experiment in India*, empirically examines how an innovative text message based information service providing daily price information to market participants in rural India is affecting geographic price dispersion across commodity markets.[1] Access to mobile phones has been shown to reduce geographic price dispersion for agriculture commodities traded in rural markets (Jensen, 2007, 2009; Aker, 2008a,b; Aker and Fafchamps, 2010; Aker and Mbiti, 2010; Aker, 2010). We extend this research by examining whether providing reliable and unbiased information via text message to interested parties can further reduce geographic price dispersion, over and above the effect observed with access to mobile phones. India's wholesale markets for agricultural produce provide a fertile environment in which to empirically test these hypotheses. In October 2007, Thomson Reuters introduced a text message (SMS) based information service in India called Reuters Market Light (RML) which provides crop-related information to market participants on a daily basis in the form of prices for local markets. Utilizing a dataset I collected in collaboration with Thomson Reuters during a three-month visit to India, we investigate how this information service is affecting (1) price dispersion over and above mere access to mobile phones and (2) crops with varying perishability levels and different supply chain characteristics.

[1]This chapter forms the basis of Parker et al. (2012).

Exploiting a natural experiment where bulk text messages were unexpectedly banned across India for twelve days, this chapter first measures the effect of the service provided by RML on geographic price dispersion. We observe a statistically and economically significant 7.6% increase in price dispersion during the text message ban. When the RML price information service is restored, price dispersion returns to pre-ban levels. Price dispersion increases during the ban are largest in areas where RML has the largest number of subscribers, lending further evidence to our claim that the loss of RML price information during the ban caused an increase in price dispersion and demonstrating that even relatively low levels of subscriber penetration have impacted price formation in the Indian agriculture markets. Price dispersion increases are concentrated in crops with highly perishable and perishable crops but not in non-perishable crops. The research provides evidence that fair and unbiased information can be beneficial in creating more efficient agriculture markets, over and above access to mobile phones. Based on the results, international aid organizations should direct funds toward services that utilize existing technological infrastructure to provide information to farmers in addition to providing broader access to information and communication technologies (ICTs).

Chapter 4, *Developing Electronic Markets in Low-Tech Environments: India's Agriculture Markets*, draws on my interactions with market participants along the supply chain, government agents charged with enforcing market rules, and RML top management in India.[2] We describe the technology involved in collecting and disseminating the price information used by Thomson Reuters, highlighting the difficulties involved with setting up a successful and impactful information system where low-tech solutions are the primary price discovery method, and the way in which Thomson Reuters overcame these challenges. Additionally, we provide a brief summary of recent research on the benefits of using technology in agricultural supply chains.

Following the examination of technology use in Indian agriculture, I turn to the impact technology has on markets in developed economies for the final two research chapters. Chapter 5, *Launching Successful E-Markets: A Broker-Level Order Rout-*

[2]This chapter forms the basis of Parker and Weber (2011).

ing Analysis of Two Options Exchanges, empirically tests how characteristics of brokers can be used to predict their order routing decisions to two competing electronic exchanges.[3] New e-markets try in a number of ways to attract a critical mass of participation and usage. Two innovative, all-electronic options exchanges, the International Securities Exchange (ISE) and the Boston Options Exchange (BOX), opened for trading in 2000 and 2004. In contrast to rival floor markets, they offered immediate order execution, direct user access, and reduced costs. ISE and BOX grew trading volumes and won market share from four incumbent exchanges in the U.S. including the largest, the Chicago Board Options Exchange (CBOE). We observe significant differences between broker order routing practices between ISE and BOX. While more brokers sent orders to BOX, they sent lower percentages and were much more likely to stop sending orders to BOX than to ISE.

To explain the markets' trading volume patterns, we develop hypotheses about new market growth, which we test using a panel of six years of quarterly disclosures from 24 major brokerage firms. We find that membership affiliations are the dominate force in predicting brokers' order routing patterns. In contrast to prior research, network externalities, as measured by an exchange's previous quarter market share, are not significant predictors after controlling for temporal heterogeneity. The results highlight the importance of factors beyond traditional network effects in explaining new market growth. Creating and maintaining the correct affiliation incentive structure is imperative to drive e-market use. Strategies that target a broad base of brokers may not benefit from the network effects as much as previously thought. Management of electronic markets should take this into consideration when designing and updating their affiliation structures.

Chapter 6, *How IT Can Disrupt Markets: A Simulation Analysis*, examines information technology-enabled trading practices that may negatively impact the entire market.[4] On one hand, the move to electronic exchanges has made markets more competitive, with multiple, usually High Frequency Traders (HFTs) becoming the key source of liquidity. The resulting competition between HFTs has led to

[3]This chapter forms the basis of Parker and Weber (2012a).
[4]This chapter forms the basis of Parker and Weber (2012b).

lower bid-ask spreads and larger book depths which have lowered direct and indirect transaction costs. On the other hand, current financial market regulation and the incentives schemes offered by exchanges to HFTs to trade, break down during times of low liquidity. At these specific moments in time, HFTs remove order flows resulting in even less liquidity exactly when liquidity is needed the most. This positive feedback loop exacerbates the instability of market prices leading to large "flash crashes" such as the one that occurred May 6, 2010 when indices fell by 9% in five minutes with some stocks falling by more than 90%. It appears that, at least under certain conditions, high frequency trading can lead to securities market aberrations, and curbs on computer-driven trading may be warranted. A group of exchanges in the US have proposed a new electronic exchange "limit up limit down" policy aimed at maintaining liquidity in markets when it is most needed. Data for these types of crashes are uncommon in reality so we simulate a simple yet realistic equity market. We analyze how current trading rules at different exchanges compare to the proposed policy and a policy which mandates maximum spreads in terms of market quality and profitability of high frequency traders during these times of high volatility. Our results show that neither policy dominates and each can result in a reduction in market quality relative to the status quo. This highlights the importance of creating proper incentive structures to ensure market quality and prevent future flash crashes. My thesis concludes with directions for future research, specifically related to the use of technology to improve operations management and markets in developing economies.

CHAPTER

2

LITERATURE REVIEW

This chapter provides a relatively brief review of the literature relevant to my thesis. It is not intended to be a full survey of the literature, but merely an indication of what has been researched to date. More general reviews of information systems (IS) research are provided by Banker and Kauffman (2004) in an overview of the last 50 years of IS research in Management Science and Standing et al. (2010) covering 196 papers over twelve years of research on e-markets.

2.1 IT and Market Pricing

In this section, we examine how IT impacts the formation of market prices. We begin with a short review of analytical information economics/costly search models. We then discuss related empirical literature as categorized into three broad streams: (1) information economics, (2) information systems, and (3) IT in developing economies.

2.1.1 Analytical Models of Costly Search

The "law of one price" predicts that the 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.

Analytical price dispersion research relaxes the assumptions of perfect, symmetric, costless information to explain observed price dispersion. By relaxing the assumption that gathering price information is costless, price dispersion has been shown to be a possible equilibrium in a competitive market (Stigler, 1961). Furthermore, price dispersion increases as the cost of acquiring price information increases.

The cost of acquiring information is not the only way to increase price dispersion in costly search models. Models have predicted numerous other ways in which price dispersion can persist in equilibrium. Stahl II (1989) finds that Nash Equilibrium price dispersion becomes more monopolistic as the number of stores increases indicating that competition may not, in itself, lead to lower levels of price dispersion. Stahl II (1996) presents a second model where price dispersion depends on the distribution of consumer search costs more than the number of stores offering the product. Varian (1980) develops an analytical model of retailer price dispersion where sales are prevalent. A symmetric mixed strategy equilibrium exists in which retailers choose their price between the cost of production and the buyers' reservation price. Diamond (1971) develops a model of the path to equilibrium in a consumer search setting using two types of consumers searching for the same product in several stores.

Other models have attempted to explain equilibrium price dispersion by consumers' unwillingness or inability to determine the lowest price. While some market participants actively search for the best price across markets, not all consumers do. Retailers can offer different prices to take advantage of the lack of search performed by some consumers. Salop and Stiglitz (1977) develop a model where consumers differ in their level of rationality. Similarly, Baye and Morgan (2004) develop a model in which price dispersion exists in equilibrium due to consumers' bounded rationality. The model shows that even small amounts of bounded rationality result in price dispersion. The model is consistent with observations seen in two independent lab studies and with data from the internet.

2.1.2 Information Economics

Empirical information economics research tests analytical models of price dispersion and suggests alternative explanations for the existence of equilibrium price dispersion.[1] Papers have traditionally relied on retail or posted-price situations and has been found to exist in a broad range of products and competitive markets. For example, Abbott III (1989) documents price dispersion for 2,430 products in the U.S. manufacturing sector. Price dispersion exists in all products with over five percent of the products exhibiting price dispersion of over 226 percent. Sorensen (2000) examines price dispersion in prescription drugs and finds that prescriptions which are repeatedly purchased exhibit lower levels of price dispersion than infrequently purchased prescriptions. The results are consist with costly search models in that the cost of searching longer is spread over all future purchases.

Other papers claim that strategic pricing by firms creates price dispersion. Ellison and Ellison (2009) argue that firms will hide the true cost of their product either through complicated product descriptions, the need for add-ons, stocking a large variety of similar products and a "bait and switch" technique where the retailer draws in customers with low cost products but convinces consumers to buy higher cost products. Evidence of these pricing strategies are found in an online price aggregator for computer memory modules. Similarly, Giulietti and Waterson (1997) find pricing strategies used by Italian grocery stores that are consistent with price discrimination due to the exploitation of customers' switching costs. The results provide evidence for the existence of a monopolistic form of price dispersion in multi-product retailers.

[1] See Baye et al. (2006) for a summary of empirical studies on price dispersion.

Baye et al. (2004b) find evidence that firms which list on price comparison websites use a "hit-and-run" pricing strategy in which they frequently chance their prices from very low to very high. In doing so, the firms can avoid the Bertrand price competition equilibrium. Lach (2002) finds similar results for four products across several stores in Israel. After controlling for store and time effects, stores frequently move between quartiles of the price distribution.

In contrast to the predictions of Stahl II (1989), but in line with Bertrand competition, Lewis (2008) finds that gasoline prices in San Diego exhibit lower levels of price dispersion when gas stations are more concentrated. Barron et al. (2004) reach a similar conclusion for gasoline stations across four geographically distinct areas. Evidence of the benefits of competition in reducing price dispersion is not limited to gasoline prices. A large empirical study using daily observations covering over 1000 products from Shopper.com finds price dispersion is an equilibrium (Baye et al., 2004a). The difference between the lowest and second to lowest prices, "the gap," decreases with the number of firms listing that product. The gap is a good measure of price dispersion in setting where Bertrand competition occurs.

2.1.3 Information Systems

While information economics research has examined the potential reasons for equilibrium price dispersion, IS research emphasizes the role that technology plays in creating more accessible markets, increasing efficiency, and improving outcomes for participants (Bakos, 1997; Malone et al., 1987). Lower coordination costs and reduced buyer search costs that occur as a result of improved information flows from IT advancements will lead to an increase in electronic markets (Malone et al., 1987; Bakos, 1991). Anecdotal evidence of the benefit that technology plays in making markets efficient dates back to the 1840's (du Boff, 1980). With the introduction of the telegraph in U.S. business ushered in a new era of commodity price arbitrage and cheaper/faster information dissemination.

Empirical research into electronic markets generally compares new electronic markets to traditional, manual markets. Clemons and Weber (1990) look at the

London Stock Exchange's transition from manual floor trading to electronic screen trading. Technology enabled trading led to increased volumes and an increase in the number of market makers. In addition, geographic barriers to trading non-UK equities on the London exchange were lowered. Even with the potential benefits, the rapid transition to e-markets does not always occur. Hess and Kemerer (1994) follow an introduction of computerized loan origination systems and find that the markets are relatively unchanged after over a decade of use.

Retail markets can also achieve the benefits of electronic intermediation. In a business to consumer (B2C) context, Brynjolfsson and Smith (2000) compare price levels and dispersion in books and CDs between physical and internet sales channels. Prices are lower online but the impact on price dispersion is dependent on the measure used. Online retailers make more frequent changes to prices and do so at smaller increments than physical stores, possibly due to reduced menu costs online. Rather than examining posted prices, Ghose and Yao (2011) examine price dispersion using transaction prices from GSA Advantage, a U.S. government business to business (B2B) market with both online and offline markets. The benefit of using transaction prices is that strategic pricing techniques, such as bait and switch, are no longer a potential explanation for price dispersion. Price dispersion still exists but is found to be lower in the electronic market.

Another line of research examines the impact that internet shopbots, which aggregate price and product information for online consumers, have on prices. In the highly commoditized book market, shopbot consumers still care about retailer branding (Smith and Brynjolfsson, 2001). Major retailers can command a higher price than relatively unknown retailers. (Tang et al., 2010) find that an increase in shopbot usage is associated with an increase in price levels and a decrease in price dispersion.

Marking the transition of comparing online and offline prices, Overby and Forman (2011) look at price dispersion in simultaneous physical and online auctions for used cars in the US. As more buyers use the online channel for purchasing, price dispersion decreases but average price stays the same. In the same context, Overby and Jap (2009) find that cars of lower quality uncertainty are sold in the electronic channel as online bidders are relatively sure they are not purchasing a lemon. Rare vehicles are also more likely to be sold and bought electronically. Arbitrage opportunities are still available in the automobile auction market but are becoming increasingly harder to find as electronic trading leads to better matching of buyers and sellers (Overby and Clarke, 2012).

2.1.4 IT in Developing Economies

IT has also been used to make markets more efficient in developing economies with research in this area concentrating on agriculture markets due to the importance of agriculture in these countries. Most research in this area focuses on the roll out of a technology that can be used to gather price information.[2] In this context, researchers assume that agents acting in the market use the new information system to gather price information and strategically decide where/when to buy/sell.

In a seminal analysis of the impact of mobile phones on geographic price dispersion in Indian agriculture, Jensen (2007) considers dispersion of fish prices across 15 approximately equidistant markets along the coast of Kerala, India. He tracked prices in these markets for six years coinciding with an introduction of mobile phone service roll-out in the area. The introduction of cell phone service resulted in a decrease in price dispersion, a near elimination of waste and higher consumer and producer welfare. Due to the phased introduction of mobile phone service and the resulting phased reductions in price dispersion, many alternative explanations can be soundly ruled out.

The impact of mobile phone service on markets has also been observed in grain markets in Niger (Aker, 2008a,b). In this setting cell phone service was gradually phased in throughout Niger in a manner similar to Jensen (2007). The findings suggest a decrease in price dispersion across markets of at least 6.4 percent, and a more efficient outcome. Introduction of cell phones may also have lessened the impact of the 2005 food crisis showing one of many unintended consequences of mobile

[2]See Jensen (2009) and GSMA (2008) for reviews of the research in this area.

phone introduction.[3] Labonne and Chase (2009) survey farmers in the Philippines in 2003 and 2006 and associate mobile phone ownership with an increase in per capita consumption. In addition to these papers, farmers are reporting multiple other benefits to mobile phone access for agricultural market participants including improved decision making on when to sell their produce, an increase in bargaining power, improved crop quality and yields, improved production decisions, and help in deciding which crops to cultivate (Mittal et al., 2010).

Two research papers based on new options for market participants in India showed that coordination benefits provided by IT are not limited to cell phone usage. Electronic auctions are reducing the advantage that intermediaries had over the farmers in the Indian coffee market. When compared to local market or "mandi" auction prices, the electronic auctions result in four percent higher prices (Banker and Mitra, 2005, 2007). Internet kiosks providing farmers with price information and hubs with better quality detection measures have been introduced into the India soybean market (Goyal, 2010). The result is an increase in the wholesale price of soybeans as well as evidence of an increase in the cultivated area used for soybeans. While intermediaries are negatively impacted by internet kiosk introduction, this is offset by a large gain for farmers, resulting in a net welfare gain.

In areas where IT is even less prevalent than in India, radio is being put to use for agricultural market price dissemination. Ugandan maize market prices are collected and broadcasted weekly over the radio, impacting the farm-gate prices that farmers receive (Svensson and Yanagizawa, 2009). Families with radios and in areas where the service is offered received 15 percent higher prices for their produce.

2.2 E-Market Diffusion and Competition

The move to electronic markets has led researchers to determine how best to introduce new technologies to ensure successful diffusion and use.[4] Interdependent

[3] A great example of an unintended consequence is shown in Aker et al. (2010). Mobile phones were originally introduced to create easier communication but are shown to improve literacy rates in Niger.

[4] Hall (2004) provides a concise summary of innovation and diffusion covering economic, social and institutional determinants of diffusion.

adoption decisions and network effects can delay the diffusion of new information technologies and prevent organizations from realizing IT's value. When technological progress does diffuse into the operational processes of acquiring firms, researchers have sought to identify the economic and sociological drivers of adoption (Abrahamson and Rosenkopf, 1997; Brynjolfsson and Kemerer, 1996; Griliches, 1957; Weber, 2006).

Empirical data has been used to understand the diffusion process of technological innovations. The seminal work of Griliches (1957) found the diffusion pattern of new, hybrid corn seeds varied by region within the central United States in the period 1932-1956. The adoption of hybrid corn, a new technology, was shown to be a series of interdependent developments involving seed producers and farmers that occurred at different rates in different areas that had different characteristics.

Empirical work looking at IT innovations generally confirms the presence of network effects that influence the expected benefits from a new technology, and thus drive adoption decisions by users. The role of network effects was identified in a study of ATM adoption by banks in the period 1971-1979 (Saloner and Shepard, 1995). At the time, technology was proprietary and ATMs were not yet linked into multi-bank networks. Controlling for a bank's deposit base, it turns out the size of the bank's branch network explained a bank's speed in rolling out ATM machines. More branches led to less rapid ATM adoption. The results suggest predictability in diffusions across firms, and confirmed that anticipated network value leads firms to be earlier adopters of a new technology. A more recent study looks at internet banking adoption and finds that customers are more likely to adopt when local online banking penetration levels are higher (Xue et al., 2011). Brynjolfsson and Kemerer (1996) identified features of spreadsheet software that commanded premium prices, but also identified "positive network externality effects from installed base and from compatibility [that are] as important as any of the intrinsic product features" of the 93 competing software packages in the sample. A study of the ISE in the period 2001-2004 showed brokers' use was positively related to whether the firm is an online broker, its ISE membership status, and the prior period's overall ISE market share (Weber, 2006).

One challenge for research studying the take up of new IT is that analyses based on sales of an IT product often overstate the true diffusion process (Fichman and Kemerer, 1999). An "assimilation gap" has been identified between the acquisition of software and its deployment. This leads to the conclusion that IT innovations may enjoy robust sales, yet are "not genuinely diffusing in the sense of having a significant impact on the operational processes of acquiring firms". Examining the assimilation of software process innovations in 608 corporate IT departments, Fichman and Kemerer develop a model with five variables including department size, education, and internal training activity. The model explained 49 percent of the variance in firms' use of software process innovations (Fichman, 2001). Devaraj and Kohli (2003) studied a sample of DSS usage in eight hospitals. Evidence of benefits were shown to be more strongly linked to the actual usage of technology than to its mere availability. Pac et al. (2010) extend the Bass diffusion model to a competitive environment in which the rival "platforms" have differing network externalities. The optimal adoption times for users are solved for as Nash equilibria, and the paper shows that under competition, the dominance of an incumbent platform translates into lagged response by users to an entrant's innovation.

In contrast to the diffusion economics literature, sociological research emphasizes how know-how or experience with an innovation can be spread across users and become the mechanism that drives network effects (Rogers, 1976, 2003). Abrahamson and Rosenkopf (1997) propose a theory of how the structure of social networks affects the extent of an innovation's diffusion among members. According to the theory, success is a result of knowledgeable advocates, experts and technology vendors promoting early adoption of an innovation. As it becomes more widespread, other forms of institutional pressure — business partners, consultants, etc. — persuade other, similar firms to adopt. They propose that as innovations gain managerial attention, becoming fads and fashionable, their diffusion accelerates, perhaps more so than would be justified on economic benefits alone.

Unlike much of the diffusion literature, IS research has traditionally focused on pricing, transactions costs, and auction mechanisms (Bakos, 1997; Ghose and Yao, 2011; Overby and Jap, 2009; Tang et al., 2010). A survey of e-markets papers appearing in top journals from 1997 to 2008 found that 90, or nearly half of the 196 papers covered, were on auctions alone (Standing et al., 2010). There is an apparent gap in the literature dealing with issues of successfully opening e-markets.

2.3 The Structure of Trading in Electronic Markets

Empirical research into market mechanisms has traditionally focused on "normal" trading times, largely ignoring days which are considered aberrations. Amihud et al. (1990) study 12 individual stocks trading on the Milan Stock Exchange from January 2, 1984 - April 30, 1987 and find that opening the market with a call auction results in lower volatility than opening the market in a continuous market. Amihud et al. (1997) study a group of stocks on the Tel Aviv Stock Exchange that were transferred from call auction trading to a call auction followed by continuous trading. These stocks received a permanent price appreciation of approximately 5.5% after 30 days under the new mechanism providing further evidence that mechanisms matter.

The benefit of exchanges going electronic is also not limited to the primary exchange. Hendershott (2005) uses a unique dataset to examine how transparency on an alternative exchange impacts pricing on a primary exchange. They study the impact of Island, an electronic communications network (ECN), removing its limit order book display to all customers. They find that the exchange-traded fund (ETF) market experiences worse price discovery and increased trading costs as a result. When Island finally showed its book again, price discovery and trading costs improved but not enough to offset the earlier worsening.

Clemons and Weber (1997) use a detailed computer simulation to examine how technology-enabled alternative trading systems impact the pricing in traditional markets. They find that electronic markets can improve efficiency while at the same time reducing information to market participants which hinders the price formation process. Schwartz and Weber (1997) provides additional simulation evidence but allows for live human interaction with the simulation. The emphasis is on how live market participants trade in order-driven trading compared to combined dealer/quote driven market. Traders submit limit orders, trading costs are reduced and dealers have less profits in the order-driven market. They observe that dealers can still benefit if volume increases or if they have an informational advantage.

Even without considering periods of large volatility, the shift to electronic markets may not be as beneficial as previously thought. Barclay et al. (2003) find that electronic markets do not always have the best market quality by comparing trades with market makers with those on ECNs. Using a month of NASDAQ trades for 150 stocks, they find that ECNs have higher ex-ante transaction costs than trades done with market makers and argue that this is the result of market maker preferencing. Similarly, Venkataraman (2001) finds that execution costs are higher on the Paris Bourse than on the NYSE which, at the time of the study, was a traditional floor-based trading structure.

Electronic markets have also enabled high frequency trading (HFT). The speed advantage of these traders allows them to process information before their slower counterparts. In an analytical model, Biais et al. (2011) show that the adverse selection problem results in significant negative externalities for non-HFT traders and decrease welfare in the market as a whole. However, in a competing analytical model, Cvitanic and Kirilenko (2010) show that a market with an HFT exhibits lower volatility than a market without the HFT. Finally, Jovanovic and Menkveld (2011) develop a model that shows market quality could either increase or decrease in the presence of HFTs. A calibrated model shows that the detrimental effects of HFT are outweighed by the positives resulting in an increase in welfare.

The majority of empirical papers agree that HFTs have led to an increase in market quality overall. In line with the analytical results of Cvitanic and Kirilenko (2010), HFTs have been shown to decrease intraday volatility (Brogaard, 2012). Similar results are obtained by Groth (2011). During the one week period in 2007, HFTs did not lead to an increase in volatility on Xetra as has been suggested by many politicians and the popular press but to decreased volatility. Similar results are reached in two papers using NASDAQ data (Hasbrouck and Saar, 2010; Hendershott and Riordan, 2011).

There is by no means consensus that HFTs are improving market quality. In a study of the May 6, 2010 flash crash, Kirilenko et al. (2011) find that HFTs were not responsible for the crash but contributed to the problem by removing liquidity at key moments throughout the day. Zhang (2010) find a correlation between HFT and market volatility suggesting that HFTs exacerbate volatility leading to lower market quality.

CHAPTER 3

IS IT ACCESS ENOUGH? EVIDENCE FROM A NATURAL EXPERIMENT IN INDIA

3.1 Introduction

The rapid and widespread growth of information and communication infrastructure in Africa and Asia has created a number of opportunities for economic growth and development (Aker and Mbiti, 2010; Mittal et al., 2010). Several recent studies have documented the use of mobile phones by farmers and fishermen in rural areas of the developing world to access information on the price of agricultural commodities in local markets (see Jensen, 2009). With access to such information, farmers can better decide where to sell their produce - shifting supply from low to high price markets to exploit price variation across markets, as well as when to sell it - delaying or bringing forward the harvesting or selling of crops to exploit price variation over time.[1] Better access to information yields more precise matching of supply and demand, resulting in more efficient markets and less variation in prices.[2] Two recent studies (Jensen, 2007; Aker, 2010), show that the introduction of mobile phone coverage causes a permanent decrease in geographic price dispersion due to improved informational flows.

Research to date implicitly assumes that the barrier to information acquisition is the prohibitive cost of communication, i.e. once communication costs are reduced by novel technologies such as mobile phones, information becomes readily available. Of course being able to communicate cheaply does help with information dissemination, but is it sufficient? It is easy to imagine that farmers living in small rural communities might have easy access to mobile phones but might have limited access to informed and non-conflicted parties from which they can obtain reliable, accurate and up-to-date information. The primary goal of this study is to empirically investigate whether the existence of a third-party information provider, on whom farmers can rely for unbiased and reliable information, 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 information and communication technology (ICT) such as mobile phones.

This is an important question because vast amounts of resources are being spent in order to improve the efficiency of agricultural supply chains in the developing world. For example, the International Development Association, a World Bank fund serving the needs of the poorest countries, alone spent close to $100M per year to this end in 2005-2009 (World Bank, 2009). If access to high quality information is important to alleviate poverty, then developing ICT applications which provide information should be a priority area within this spending category. Also, if access to high quality information has a differential impact on market efficiency depending

[1] Besides such arbitrage benefits, access to price information might also benefit farmers by improving their bargaining power vis-à-vis intermediaries (Jensen, 2009).

[2] While a decrease in price dispersion does not necessarily translate into an increase in farmer welfare (see Jensen, 2009), the general assumption is that stable commodity prices benefit producers as well as consumers (see Newbery and Stiglitz (1981) for a general treatment and Poulton et al. (2006) with regard to food prices in the developing world).

on operational characteristics such as crop perishability, then this should be taken into account to optimize spending. Additionally, despite widespread press coverage of the use of mobile phones in Africa and Asia (e.g. Economist, 2011) and mobile phone penetration levels in the developing world estimated at 68% in 2010 (World Bank, 2011), penetration in rural areas is much lower. For example, in rural India it is estimated to be as low as 23% (Hindu, 2011). Funding agencies such as the World Bank continue to invest large sums building information and communication infrastructure targeted at bridging this gap. While the World Bank spent $4.2 billion in support of the ICT sector in 2003-2010, much of this money was spent on improving access to mobile phones and the internet, and a relatively small amount was spent on ICT applications that would improve information quality (see World Bank, 2011; USAID, 2010). If significant leaps in the matching of supply and demand can be obtained via providing better information, over and above wider access, governments and funding agencies should direct funds accordingly.

To answer this question we utilize a detailed, market level 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 daily mobile phone text messages that are sent in bulk to its paying subscribers. Investigating the impact that RML information has on price dispersion is a complicated empirical problem. RML chooses the crops and markets for which it provides price information. A potential source of endogeneity would be RML managers choosing to offer the service in areas with large price dispersion. The benefit is largest in these areas and should therefore result in a larger number of subscribers. A second source of endogeneity comes from the subscribers' choice of the markets to obtain price information for. Subscribers will find the price information service most beneficial in areas with large levels of price dispersion. With either of these endogenous choices, price dispersion may be highest in areas where RML has the largest number of subscribers. One possible solution for these sources of endogeneity is to perform a randomized controlled experiment. However, this type of experiment requires that large parts of the country be without RML. Additionally, farmers across India share information with neighbors, family and friends leading to a weak experiment. A more promising strategy is one which identifies an instrumental variable. Early stages of our research identified cell phone service disruptions as a possible instrumental variable, but the necessary data proved too difficult to obtain.

On September 23, 2010, RML experienced a major service disruption when bulk text messages were unexpectedly banned throughout India in advance of an Allahabad High Court verdict that was to be announced on September 24. The case in question concerned a land title dispute for a piece of property in the city of Ayodhya, Uttar Pradesh, India that is claimed to be a holy site by both Hindu and Muslim religions. Deadly protests and political unrest surround the history of the site. In an attempt to reduce the likelihood of rumors spread via text message and technologically coordinated riots, the Ministry of Communications & Information Technology of the Government of India directed telecommunication providers to immediately stop sending bulk text messages throughout India on the evening of September 22, 2010. The ban was unexpected by RML and all other market participants when it went into effect on September 23, 2010. After multiple delays in announcing the verdict and corresponding extensions of the text message ban, the government lifted the ban at the end of October 4, 2010 and operations at RML returned to normal on October 5, 2010. For the twelve days from September 23, 2010 until October 4, 2010, RML subscribers received no price information through the service.

The bulk text message ban was an unexpected, exogenous shock, completely unrelated to prices in markets except through the information provided by RML. All other sources of information retrieval, including traveling to the markets, calling markets, asking friends, family and fellow market participants, or checking prices through the internet were still in effect. This provides a natural experiment econometric specification which removes concerns for endogeneity.[3] After controlling for market and temporal heterogeneity, we find that the average geographic price dispersion, measured as the log of the standard deviation of prices for a crop in a group

[3]See Angrist and Krueger (2001) for more information and a summary of natural experiments in the economics literature through 2001.

of markets on a day, of 170 crops across 13 states increased by 7.6% (95% C.I. of 2.3 to 12.8%) 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 occurs in groups of markets where RML has the largest number of subscribers, providing further evidence that the increase in price dispersion was caused by the loss of RML information.

Due to the difficulty in collecting data, research to date on demand-supply mismatch in agricultural supply chains has primarily focused on one or at best two agricultural commodities in a limited number of markets that were chosen to be as homogeneous as possible to reduce concerns regarding correlated omitted variable bias. Therefore, comparisons on how valuable information is depending on operational characteristics such as crop perishability have been limited. The richness of our dataset allows us to investigate these issues. We find that while both highly perishable crops (such as banana, coriander, or okra) and crops with intermediate perishability (such as apple or pomegranate) exhibit lower price dispersion when price information is available via RML, non-perishable crops (such as wheat, soybean, or lentils) are not impacted. Furthermore, we investigate the managerially important question of whether groups of markets with a large number of customers are different from groups of markets with a low number of customers.

Our research contributes to the literature on how information and communication technologies impact rural supply chains in the developing world. We show that improvements in such technologies are not by themselves sufficient to ensure access to the best information. Organizations that utilize the ICT infrastructure to provide reliable, unbiased and up-to-date information can further contribute to reducing price dispersion. Our research also throws light on how such ICT applications affect crops with different perishability characteristics.

Besides making an argument for complementing investment in wider access to ICTs with investment in creating third party information providers that have the operational infrastructure and organisational capability to collect, verify and transmit information through existing ICT infrastructure, our work has 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 do make a difference in the functioning of agricultural crop markets in the developing world. It is therefore understandable that this business model is proliferating.[4] Furthermore, our research provides specific advice on which types of crops to cover by such as service to provide the largest benefit for their customers. This can help such organizations to focus their operational and marketing efforts. It can also inform development organizations what types of crops to target when they fund such work.

3.2 Relevant Literature

In the operations management literature on demand-supply mismatch in multi-product or multi-location firms, a mismatch can occur when a firm stocks too much of some products and too little of others, or if it stocks too much of a particular product at one location, and too little of it at another (e.g. Fisher and Raman, 1996; Cachon and Olivares, 2010; Randall and Ulrich, 2001; Cachon and Terwiesch, 2008). In contrast to such firms, farmers in developing countries typically do not have enough scale to sell their produce at multiple locations simultaneously. For such farmers, two important day-to-day operational decisions that affect the matching of supply and demand are which market to take their produce to, and whether to delay or bring forward the sale of produce.[5] Better matching of supply and demand at the level of individual farmers should aggregate up to more efficient markets, and

[4]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 as well as other developing countries. Examples in India include IKSL, a partnership between the Indian Famers Fertilisers Cooperatives and Bharti Airtel, an Indian mobile operator (Mittal et al., 2010), Fisher Friend, a programme 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`). 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`). 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 MTNm a mobile phone operator, which operates in Uganda and Ghana (`http://www.google.co.ug/africa/trader/home`) and CellBazar in Bangladesh (`http://corp.cellbazaar.com`).

[5]Farms in the Western world tend to be larger and more vertically integrated into downstream agri-industries, and face different decisions.

reduced price dispersion.

The "law of one price" predicts that the 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.

Of particular relevance to our study is a subset of the literature that investigates the impact of new information and communication technologies 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 information and communication technology 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). The literature sets out to empirically estimate whether prices, and more importantly for the purposes of our study, price dispersion are affected as buyers and sellers start using newer technologies.[6]

Previous research has shown the role of ICTs and ICT-enabled services in reducing price dispersion. Brynjolfsson and Smith (2000) compare 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 fair and unbiased aggregators of price information in a similar way that RML provides price information. Overby and Forman (2011) demonstrate that the use of electronic

[6]Note that not all theoretical models of price dispersion agree that a reduction in search costs will result to lower price dispersion (e.g. MacMinn, 1980). Indeed it is easy to construct examples where this is not the case. Consider a setting where multiple identical firms sell in only one location each. Each location has a single customer whose search costs are infinite. In such a setting firms will enjoy (local) monopoly power leading them to charge monopoly prices which in turn would result in spatial price dispersion of zero. Lowering the search costs so that some (but not all) customers find it profitable to search will induce competition between some of the firms which will result in them charging prices that are (weakly) lower than monopoly prices and thus generate some price dispersion. 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 price dispersion.

channels alongside physical channels for selling used vehicles reduces spatial price dispersion. Nevertheless, there is ample evidence to suggest that the advent of new information and communication technologies does not completely eliminate price dispersion. Gatti and Kattuman (2003) measure online price dispersion of 31 distinct 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. (2004a) 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., 2004a), consumers' failure to internalize additional costs such as shipping fees (Einav et al., 2011) or deployment of "obfuscation strategies" such as bait-and-switch by firms (Ellison and Ellison, 2005, 2009).

Since price dispersion is so pervasive despite advances in information and communication technology, it is not surprising that we find significant spatial 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 mere 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 reliable and timely information delivered to farmers over and above access to mobile phones while Tang et al. (2010) examine the benefit of reliable and timely information delivered via automated shopbots to consumers over and above mere access to the internet.

At least three studies have looked at the impact of mobile phones on 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 spatial price dispersion that occurred after the introduction of mobile phones. Aker (2010) reports that the introduction of mobile phones in Niger results in a 10% decrease in grain price dispersion across 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. Furthermore, since we utilize a natural experiment for identification, our work provides additional evidence on the efficacy of information and communication technology in reducing price dispersion.

The third study, by Aker and Fafchamps (2010), using a similar dataset to Aker (2010) compares the impact of introducing mobile phones on price dispersion of a semi-perishable crop (cowpea) 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. Furthermore, they find that the effect is concentrated in markets that are more than 350 kilometers apart, linked by unpaved roads and are outside of the harvest period. We complement their study by examining a range of different crops. This allows us to verify that differences in price dispersion decreases 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 their e-choupal program, they also offer farmers the option to sell directly to the company for a pre-agreed price and quality (Devalkar et al., 2010). Goyal (2010) reports an 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 significant 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 (2011) work with Thomson Reuters to conduct a randomized experiment where they give the RML service to farmers in some villages in Maharashtra but not others over a year. While the farmers claim to use the RML information, there is no statistical evidence that RML did influence 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 are interested in aggregate market efficiency as measured by geographic price dispersion. We therefore do not measure farmer level prices and volumes.

3.3 Indian Agricultural Markets and Data

In what follows, we introduce the specific challenges faced by market participants in Indian agriculture and provide an overview of our empirical context. For a more detailed description of Indian agriculture and some historical perspective, see World Bank (2008) or Thomas (2003). A recent analysis of Indian agriculture markets including pictures of current market practices and links to videos of the produce supply chain in action is provided in Chapter 4. We augment these studies with personal observation, site visits and conversations with RML's top management, agricultural experts, content managers and marketing/advertising employees as well as farmers, traders, and government officials in agriculture positions.

3.3.1 Indian Agricultural Supply Chain

Most Indian states are regulated in accordance with the national government's Agricultural Produce Marketing (APM) Act. The APM Act enables the state to regulate spot markets, called "mandis," which operate under the direction of the State Agriculture Marketing Boards (SAMBs) and Agricultural Produce Marketing Committees (APMCs) at the local level. An APMC's primary functions are establishing and managing markets, as well as managing the licensing of traders within these markets.

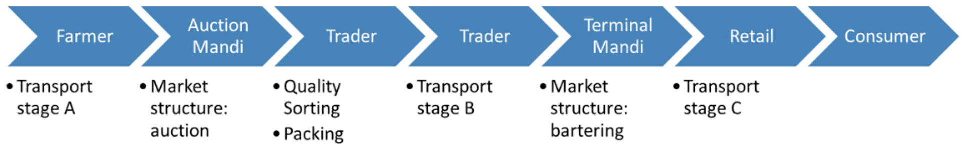

Figure 3.1: India's agricultural supply chain.

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India's agricultural spot markets are either auction markets or terminal markets. In auction markets, farmers sell to traders through an auctioneer employed by either the APMC or a commission agent who is responsible for conducting auctions, weighing produce and coordinating payment and delivery. In these markets, the farmer brings their produce to the market. They are assigned a number upon arrival and wait in the parking spot corresponding to that number. The auctioneer and an administrator lead 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 exact weight of the produce is measured and the farmer is paid according to the price set in the auction.

After produce is purchased by a trader in the auction markets, the trader's employees sort and package the produce in preparation for shipping to either domestic markets or to ports en route to international markets. Domestic markets are called terminal markets. In these markets, traders sell to wholesalers, retailers and sometimes to end consumers. The trader sets a price and the wholesaler/retailer/consumer visits different traders' stalls to barter for goods of varying price and quality.

Figure 3.1 shows an overview of the path produce takes once a farmer harvests the crop. Smaller farmers may face an additional intermediary who purchases the produce at the farmer's field, offering a "farm gate" price. These intermediaries aggregate produce from many small farmers and then sell it at the market. Similarly, some crops do not trade in markets but are solely procured by intermediaries at the farm gate or another location outside of the market. An additional level could be present downstream of the terminal market. Such intermediaries purchase produce at the terminal market, break bulk and sell to retail shops and roadside merchants that are common throughout India. The end result is that there are six to eight intermediaries between the farmer and the end consumer in the Indian agricultural supply chain versus two to three in the United States (World Bank, 2008).

3.3.2 RML Data Collection Process and Data Description

Launched in October 2007, RML sells subscriptions for crop related information to market participants, such as farmers and traders, via daily text messages sent in bulk. Subscribers receive indicative price and volume information for high quality produce for up to two crops of their choice in up to three markets of their choice for each crop. In addition to this information, they receive weather forecasts, advisory information related to crops of their choice (such as which fertilizer to use or how deep to plant their seeds) and national and international news stories three times a day.

Subscribing to RML is a relatively simple process. Prospective subscribers go to a local agricultural store where they purchase a card for a 3, 6 or 12 month subscription costing approximately Rs. 80 ($2) per month. They choose up to two crops and up to three markets for each crop, a taluka (similar to a US county) for which they would like weather forecasts and one of nine languages in which they can have the text message delivered: Bengali, English, Gujarati, Hindi, Kannada, Marathi, Punjabi, Tamil and Telugu. They place a phone call to the RML call center where the card is validated and the subscriber's choices are recorded in the RML database. The subscriber begins receiving RML text messages within two days.

To gather the price and volume information, RML sends a market reporter to each market every day that the market is open. The market reporter observes auctions in auction markets. In the terminal markets, the market reporter visits traders' stalls to collect price and volume information. The market reporter records the daily high price, low price, and volume for the highest quality produce only. Prices and volumes sent to subscribers are therefore indicative of high quality produce. Farmers with lower quality produce can expect to receive lower prices. The market reporter confirms the prices and volumes of the produce with the APMC officials at the market and either calls or sends a text message to the RML system containing the price

Crop Price Data	
Crop	Crop corresponding to the prices observed
State	State where the prices were observed
Market	Market where the prices were observed
Date	Date when the prices were observed
Low Price	Low price observed
High Price	High price observed
Volume	Total amount of crop transacted at the market
Perishability	Perishability level of the crop: High Perishability (shelf life of less than 3 days) Medium Perishability (shelf life of 4 days to 2 months) Low Perishability (shelf life of more than 2 months)
Subscription Data	
MSISDN	A subscriber identification code
State	The state where the subscriber resides
District	The district where the subscriber resides
Taluk	The taluk where the subscriber resides
Start Date	The first date that text messages were or will be sent to the subscriber for the current subscription
End Date	The last date that text messages were or will be sent to the subscriber for the current subscription
First Crop	The subscriber's first crop choice
First Markets	Up to three markets for which the subscriber has subscribed to information for the first crop
Second Crop	The subscriber's second crop coice
Second Markets	Up to three markets for which the subscriber has subscribed to information for the second crop

Table 3.1: Description of the crop price and subscription data supplied by RML. The time period covered is August 1, 2010 to November 30, 2010.

and volume information for that crop and market. After a computer flags potential errors in the prices reported by the market reporter, a chief market reporter verifies the validity of the prices for several markets, resolves any discrepancies with the market reporter and submits final price and volume information. 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 next day.

We use RML subscription and price data in our analysis. For each subscription we have 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. For each crop market day, we have the volume and high and low prices. We utilize high prices for the bulk of our analysis but ensure the results are similar for analysis using low prices as well.

We supplement the RML price and subscription data with a classification of the perishability of crops provided by an RML chief market reporter. A summary of the data is in Table 3.1.

3.3.3 Price Data Validity and Creating the Panel Data Set

Mismatch in demand and supply across markets, which results in spatial price dispersion, is a function of both observable and unobservable characteristics of buyers and sellers in an area. In India, State Agriculture Marketing Boards set the regulation for trade in markets. Hence, quality standards can be drastically different from state to state. It is therefore natural to measure spatial price dispersion within state boundaries where quality differences are arguably smaller than they are across state boundaries. Furthermore, monsoon rains, which drive crop seasonality, enter and exit states at different times.

While other studies of spatial price dispersion have examined situations where the same set of markets is open every day or week, in our case, all markets within a state are not open every day. Therefore it is not enough to include a fixed effect for each market, as the group of markets that is open on any particular day has a systematic effect on price dispersion. One group of markets may be open on one day and another, possibly overlapping group of markets may be open on the next day. We call the group of markets that are open within a state for a crop on a day the crop market cluster for that crop state day. Of course, the characteristics of the markets that are open on a day can impact price dispersion. 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 these time-invariant characteristics we include a fixed effect for each crop market cluster in our econometric specification.

The standard deviation of prices each day is a natural measure of spatial price dispersion within a crop market cluster and is a widely used measure of price dispersion (e.g. Brynjolfsson and Smith, 2000; Sorensen, 2000; Ghose and Yao, 2011; Tang et al., 2010). Using the log of the standard deviation of prices, $\log(\sigma)$ where σ denotes standard deviation, means any differences in levels attributable to specific crops or market clusters can be controlled for with crop market cluster fixed effects.

For robustness, we use two additional measures of price dispersion that are common in the literature. The first measure is the the log of the range of prices, $\log(P_{\max} - P_{\min})$ where $P_{\max}$ and $P_{\min}$ index the maximum and minimum prices across markets in a crop market cluster on a day. This measure of price dispersion has also been extensively used in the literature (e.g. Abbott III, 1989; Sorensen, 2000; Ghose and Yao, 2011).

A second measure of price dispersion is the coefficient of variation, $CV = \sigma/\mu$ where μ is the average price across markets in a crop market cluster on a day. This measure has been included for comparison to other studies of price dispersion (e.g. Abbott III, 1989; Overby and Forman, 2011). However, any effect that RML has on prices could mask the effect on price dispersion when measured using the coefficient of variation. For example, if RML allows farmers to command *higher* prices for their produce due to greater bargaining power or a reduced informational advantage for traders, then a natural hypothesis is that prices were *lower* during the bulk text message ban. If price decreases during the ban were the same in all markets, then the standard deviation would be the same. However, a lower average price combined with an identical standard deviation results in an increase in the coefficient of variation that would simply be due to the price effect of RML information.

We utilize price data from August 22, 2010 to November 8, 2010 in our analysis with a total of 257,907 crop market day observations. While we perform analysis at the crop market cluster day unit of analysis, we first handle several issues with the highly unbalanced structure of the RML price data. We conduct our analysis using a short time window around the period of the ban. There are two main reasons for doing so. First, a short time horizon allows us to minimize the impact of seasonality

	Bhindi - High Perishability			
	Mean	Stdev	Min	Max
High Price	1119.00	629.43	104.08	8998.26
Low Price	894.01	496.07	75.04	5836.51
Volume	38.49	56.85	1	900
	Onion - Medium Perishability			
	Mean	Stdev	Min	Max
High Price	1043.29	321.73	138.38	11380.15
Low Price	842.72	266.52	60.86	2101.16
Volume	950.78	3478.87	1	62000
	Bajra - Low Perishability			
	Mean	Stdev	Min	Max
High Price	749.98	217.12	142.66	1401.84
Low Price	703.88	197.36	38.46	1276.96
Volume	449.54	816.64	1	8000

Table 3.2: Summary data for three crops with different levels of perishability at the crop market day level.

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

Table 3.3: Summary data for different levels of perishability at the crop market cluster day level.

on crop prices. Second, RML is constantly adding to its portfolio of markets for which it offers the service. Over a long time frame this could mean the introduction of new markets and hence new crop market clusters. Stable crop market clusters help to accurately estimate the crop market cluster fixed effects. We therefore utilize price data from August 22, 2010 to November 8, 2010 with a total of 257,907 crop market day observations. Borrowing from event study literature, 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.

Food price inflation in India reached an annualized 18.3% at the end of December 2010 (Economic Times, 2011).[7] 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 through time. In this case we would find an increase in price dispersion during the ban and an even larger increase in price dispersion after the ban. We therefore deflate prices before applying any further filters to the data. Rather than use the government reported levels of inflation for each category of agricultural commodities - eg. lentils,

[7]For a more detailed analysis of inflation in India see World Bank (2010).

fruits or vegetables - we fit a model of log prices against a linear time trend for each crop. This model captures differences in the inflation rate for different crops. Prices are therefore measured in beginning of time window Rupees (Rs). This is in line with Jensen (2007) who uses 2001 Rs. in his analysis of fisheries in India in the period 1997 to 2001.

Sundays and holidays have fewer markets open than a typical day. We therefore remove Sundays and Gandhi Jayanti[8] (October 2, 2010) from the analysis and 257,412 crop market day observations remain.

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 only once. Removing such crop markets results in fewer crop market clusters with more observations (i.e. days) in them. We decided to remove any crop market with less than 10 observations and 254,148 crop market day observations remains. For robustness, we perform all analyses keeping all crop markets and removing crop markets with less than 20 or less than 30 observations.

Geographic price dispersion must be measured over multiple markets on a day. Observations in states with only one market open for a crop on a day are removed and 239,459 crop market day observations remain.

Using $\log(\sigma)$ as our measure of price dispersion means that the standard deviation of prices cannot equal zero. This occurs if prices for a crop in all markets in a cluster are identical on a day. We remove any crop market cluster days in which all of the markets have the same price and 238,177 crop market day observations remain.

Price dispersion in crop market clusters which are observed only once in the data would be completely explained by the crop market cluster fixed effect. Two observations is the absolute minimum we will need to estimate crop market cluster fixed effects and allows us to exploit temporal variation in geographic price dispersion. We remove any crop market clusters which have only one observation and 140,257 crop market day observations remain.

[8]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 list of holidays: `http://india.gov.in/govt/pdf/govt_holiday_list_10.pdf`.

Even in the short time period we are examining, there is still an opportunity for RML to add additional crops in certain states. 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 and 132,897 crop market day observations remain.

As discussed previously, some crops are not traded in markets - traders contact farmers directly and offer a farm gate price. Volumes for these crops are not reported to subscribers or even collected by the market reporters. These crops are systematically different from most crops in the dataset. RML gathers the price information not by observing auctions and validating prices and transacted volumes with APMC officials, but by contacting several of the traders in the area. These crops can be identified by missing volume data. We therefore drop crops with more than 5% missing volume data and 103,439 crop market day observations remain.

Table 3.2 contains summary data by crop market day for three crops of differing levels of perishability after deflating and filtering data filters. Following the deflation and filtering of crop market day observations, we convert the data to crop market cluster day observations resulting in 14,349 observations. Note that on any day, only one crop market cluster is open in each state. A summary of the crop market cluster day data is in Table 3.3.

3.3.4 Independent Variables and Controls

Crop perishability measures the extent to which crops can be stored for future use. The classification was performed by an agricultural expert and Chief Market Reporter working within RML. This classification categorizes crops as highly perishable (shelf life of less than 4 days), perishable (shelf life of between 4 days and 2 months), and non-perishable (shelf life greater than 2 months).

Number of subscribers is the sum of the number of subscriptions that are active for each of the markets within a crop market cluster on a day.

As mentioned earlier, our unit of analysis is a crop market cluster day, and we include a fixed effect for each crop market cluster. Some of the differences between crop market clusters that these fixed effects control for are crop perishability, the number of markets in a market cluster, composition of markets in terms of terminal or auction markets, proximity of markets to one another and to subscribers on average over time, the quality of transportation links between markets, storage facility availability, proximity to an international port, etc.[9]

Date dummy variables would control for any unobserved temporal heterogeneity that impacts all crop and markets. However, they cannot be included in our specification because they are perfectly collinear with the text message ban dummy variables used for identification. Instead we include day of week dummy variables to control for any systematic differences within a week.

3.4 Identifying the Impact of Information on Price Dispersion

This section presents the econometric identification strategy. We use this model specification to determine what impact, if any, a reliable and unbiased price information service has on geographic price dispersion, over and above access to mobile phones. We then perform several robustness checks to bolster our claim of causality including ruling out potential problems with the identification strategy and any alternative explanations. Finally, we discuss an extension of the empirical strategy which allows us to investigate how crops with different levels of perishability are differentially impacted by the loss of RML price information.

Investigating the impact that RML information has on price dispersion is a complicated empirical problem. RML chooses the crops and markets for which it provides price information. A potential source of endogeneity would be RML managers choosing to offer the service in areas with large price dispersion. The benefit is largest in these areas and should therefore result in a larger number of subscribers. A second source of endogeneity comes from the subscribers' choice of the markets

[9]Given the short time frame of our analysis there should be no major changes in any of the infrastructure related variables.

Bulk text message ban timeline	
September 22, 2010	In the evening, MCIT issues a directive to mobile telecom service providers to immediately stop bulk text messages for a duration of 72 hours with the option to extend the ban if needed.
September 23, 2010	Subscribers stop receiving RML text messages.
September 24, 2010	Announcement that text message ban is extended to September 30, 2010.
September 30, 2010	Allahabad High Court delivers verdict. Announcement that text message ban is extended to October 1, 2010.
October 1, 2010	Announcement that text message ban will be extended through October 4, 2010.
October 4, 2010	Ban is lifted.
October 5, 2010	Subscribers begin receiving RML text messages again.

Table 3.4: Timeline of the bulk text message ban instituted to combat the spread of rumors and coordination of riots. All of this data is from `http://pib.nic.in/newsite/erelease.aspx?relid=65915` and subsequent releases from the Ministry of Communications & Information Technology (MCIT)

to obtain price information for. With either of these endogenous choices, price dispersion may be highest in areas where RML has the largest number of subscribers. One possible solution for these sources of endogeneity is to perform a randomized controlled experiment. However, this type of experiment requires that large parts of the country be without RML. Additionally, farmers across India share information with neighbors, family and friends leading to a weak experiment. A more promising strategy is one which identifies an instrumental variable. Early stages of our research identified cell phone service disruptions as a possible instrumental variable, but the necessary data proved too difficult to obtain.

On September 23, 2010, RML experienced a major service disruption when bulk text messages[10] were unexpectedly banned throughout India in advance of an Allahabad High Court verdict that was to be announced on September 24, 2010. The case in question concerned a land title dispute for a piece of property in the city of Ayodhya, Uttar Pradesh, India that is claimed to be a holy site by both Hindu and Muslim religions. Deadly protests and political unrest surround the history of the site.[11] In an attempt to reduce the likelihood of spreading rumors and technologically coordinated riots, the Ministry of Communications & Information Technology of the Government of India directed telecommunication providers to immediately

[10]Bulk text messages are defined as more than 10 messages for an individual or more than 100 messages for a business per day.

[11]See, for example: `http://www.bbc.co.uk/news/world-south-asia-11436552` accessed on April 13, 2011.

stop sending bulk text messages throughout India on the evening of September 22, 2010.[12] The ban was unexpected by RML and all other market participants when it went into effect on September 23, 2010. After multiple delays in announcing the verdict and corresponding extensions of the text message ban, the government lifted the ban at the end of October 4, 2010 and operations at RML returned to normal on October 5, 2010. For the twelve days from September 23, 2010 until October 4, 2010, RML subscribers received no price information through the service. Full timing of the ban is available in Table 3.4.

The bulk text message ban was an unexpected, exogenous shock, completely unrelated to prices in markets except through the information provided by RML. All other sources of information retrieval, including traveling to the markets, calling markets, asking friends, family and fellow market participants, or checking prices through the internet were still in effect. Any observed increase in price dispersion during the ban can therefore be attributed to the loss of information provided by RML.

The bulk text message ban provides a natural experiment that breaks potential sources of endogeneity. 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. 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:

$$\mathrm{PD}_{ckt} = \alpha_{ck} + \beta_1 \mathrm{DuringBan}_t + \beta_2 \mathrm{PostBan}_t + \delta_d + \epsilon_{ckt} \tag{3.1}$$

where PD is the price dispersion of crop c measured across market cluster k on date t, DuringBan is a dummy variable taking the value of 1 when the bulk text message ban is in effect, PostBan is a dummy variable taking the value of 1 after the bulk text message ban has been lifted, δ_d captures day of the week differences in price dispersion, and α_{ck} measures crop market cluster specific differences.

Assuming homoskedastic error variances can result in unreliable standard errors

[12]The Ministry of Communications & Information Technology Department of Telecommunications memo can be downloaded from: `http://www.medianama.com/wp-content/uploads/DoT-Notice-on-Banning-of-Bulk-SMS-and-MMS.pdf` accessed on April 13, 2011.

and significance levels. This could lead to a rejection of the null hypothesis that there was no change in price dispersion during the ban when such a rejection is not justified (or vice versa). Previous research has acknowledged the need to make errors robust to heteroskedasticity and serial correlation (Gerardi and Shapiro, 2009). To verify that error variances are not homoskedastic, we perform two tests. First, we test for heteroskedasticity of the residual variance across crop market clusters in the model (see Baum, 2001; Greene, 2002, p. 323-324). We reject the null hypothesis of homoskedastic error variance ($\chi^2(1671) = 1.4 \times 10^{35}; p < 0.0001$) indicating that error variances across crop market clusters are not identical. Next, we test for serial correlation in the model (see Drukker, 2003; Wooldridge, 2002, p. 274-276). We reject the null hypothesis of no first order autocorrelation ($F(1, 382) = 26.707; p < 0.0001$). To correct the errors for heteroskedasticity and arbitrary within cluster serial correlation, we cluster errors at the crop level. Clustering errors at the crop level allows for correlation across crop market clusters of the same crop, a more flexible error structure than clustering at the crop market cluster level alone. In our context this is especially import as two crop market clusters may be composed of many of the same markets.

In addition to a first order effect on price dispersion during the ban, there may have been a temporal change in the variance covariance matrix of residuals during the ban. Failure to account for this heteroskedasticity could again result in unreliable standard errors. A potential option is to allow for correlation across observations within the pre, during and post ban periods in addition to crop level correlations (Cameron et al., 2011). However, cluster robust standard errors are consistent and asymptotically normal as the number of cluster groups, or crops in our case, tends to infinity. Furthermore, with multidimensional error clustering, errors are consistent and asymptotically normal when the *smallest* number of cluster groups tends to infinity. Clustering errors on the pre, during and post ban periods would result in only 3 cluster groups, well below the threshold of around 40 or 50 cluster groups suggested by previous research (Wooldridge, 2003, 2006). The alternative is to cluster errors for observations on the same date. This provides a large enough

VARIABLES	(1) $\log(\sigma^H)$
DuringBan	0.076***
	(0.027)
PostBan	0.026
	(0.035)
Observations	14,349
Day of Week FEs	YES
Adjusted R-Squared	0.877
Min. No. obs per crop market	10
Min. No. markets per cluster	2
Min. No. obs per cluster	2
Start Date	23-Aug-10
End Date	8-Nov-10
Crop Market Clusters	1671

Table 3.5: Main effect regression results. 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

number of cluster groups for errors to be reliably estimated. We therefore cluster errors in two dimensions: at the crop level and at the date level.

3.4.1 Basic Effect

The results of the regression for Model (3.1) are listed in Table 3.5. The coefficient on DuringBan is positive and significant indicating that price dispersion was indeed higher during the text message ban. Furthermore, price dispersion increases occurred during the ban only, when RML information was not available to market participants. Following the ban there is no significant change in price dispersion relative to levels seen before the ban as evidenced by an insignificant coefficient on PostBan. The interpretation of the DuringBan and PostBan coefficients is a percentage change in price dispersion meaning that an economically and statistically significant 7.6% increase in price dispersion is observed during the ban. Because other forms of obtaining price information were unaffected by the ban, this increase in price dispersion can be attributed to the loss of RML price information.

3.4.2 Number of RML Subscribers

Observing an increase in price dispersion during the ban in areas where there are a relatively large number of RML subscribers provides further evidence that RML price information is causing a reduction in price dispersion. To identify the impact of the number of subscribers on price dispersion, we calculate the number of subscribers for each market in a crop market cluster on a day. Within a crop market cluster there is little variability in the number of subscribers during our study period. We therefore find the average number of subscribers in the time surrounding the ban for each crop market cluster. We rank all crop market clusters for each crop in ascending order based on number of subscribers and calculate a within-crop percentile score for number of subscribers, for each crop market cluster. We group crop market clusters in the lowest 40% into one bucket and separate the remaining 60% into 4 buckets of 15% each. Dummy variables for each bucket are then interacted with the DuringBan variable for identification.

$$\text{PD}_{ckt} = \alpha_{ck} + \beta_1 \text{DuringBan}_t \times \text{NumSubscribersBucket}_{ck} + \beta_2 \text{PostBan}_t + \delta_d + \epsilon_{ckt} \tag{3.2}$$

where NumSubscribersBucket 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 bucket, corresponding to a percentile range within a crop, and all other variables are as described previously.

The results of the regressions for Model (3.2) are listed in Table 3.6. The significant coefficients on the two buckets corresponding to the high and very high percentiles of subscribers, 70 to 85 and 85 to 100 percentiles, confirm that RML is causing a reduction in price dispersion. Importantly, increases in price dispersion are not observed where there are a relatively low number of subscribers for a crop.

3.4.3 Alternative Explanations

Even though we have shown price dispersion increases during the ban are largest in areas where RML has the largest number of subscribers, we must rule out several alternative explanations before we can confidently conclude that RML is causing a reduction in price dispersion. One possible alternative explanation is that, as the

VARIABLES	(1) $\log(\sigma^H)$
DuringBan_VeryLow	0.072
	(0.044)
DuringBan_Low	0.052
	(0.052)
DuringBan_Medium	0.013
	(0.073)
DuringBan_High	0.110**
	(0.044)
DuringBan_VeryHigh	0.094**
	(0.038)
PostBan	0.027
	(0.035)
Observations	14,349
Day of Week FEs	YES
Adjusted R-Squared	0.877
Min. No. obs per crop market	10
Min. No. markets per cluster	2
Min. No. obs per cluster	2
Start Date	23-Aug-10
End Date	8-Nov-10
Crop Market Clusters	1671

Table 3.6: Number of subscribers regression results. 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

VARIABLES	(1) $\log(Volume)$	(2) $\log(P^H)$	(3) $\log(\sigma^H)$	(4) $\log(\sigma^H)$	(5) $\log(\sigma^H)$
DuringBan	0.001	0.037***	0.077***	0.073***	-0.005
	(0.025)	(0.011)	(0.026)	(0.028)	(0.030)
PostBan	0.051*	-0.008	0.029	0.032	0.023
	(0.030)	(0.010)	(0.032)	(0.036)	(0.048)
Observations	14,349	14,349	17,015	11,624	8,786
Day of Week FEs	YES	YES	YES	YES	YES
Adjusted R-Squared	0.939	0.991	0.872	0.877	0.842
Min. No. obs per crop market	10	10	10	10	10
Min. No. markets per cluster	2	2	2	2	2
Min. No. obs per cluster	2	2	2	2	2
Start Date	23-Aug-10	23-Aug-10	16-Aug-10	1-Sep-10	22-Aug-09
End Date	8-Nov-10	8-Nov-10	15-Nov-10	30-Oct-10	7-Nov-09
Crop Market Clusters	1671	1671	1892	1461	1153

Table 3.7: Time, volume and price regression results. Crop market cluster day panel regressions with two-way error clustering: at the crop level and at the day level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

which may be due to the November 5, 2010 Diwali festivities.

Another concern is that disruptions are limited to the area around Ayodhya. If there are a larger number of subscribers in these areas then we could be attributing the increase in price dispersion in areas with a large number of subscribers to the information provided by RML when in fact the effect is really capturing the localized disruption. We can rule out this alternative hypothesis by showing that the distance from Ayodhya is not a significant predictor of the number of subscribers. We collected geolocation data for each of the markets using Amazon Turk, a service that pays individuals around the world to answer short, concise questions. We provided the state and market name to the individuals who then told us where the market is located. Each market location was sent to two individuals. If the locations provided were close enough to each other we took this as the market location. For responses where the responses differed by more than this threshold, we re-submitted the location to two individuals again. If we did not get consensus between these two individuals, one of the authors or a research assistant verified the locations and determined which was the correct location. For locations that were not identified at all by the Amazon Turk service, one of the authors or a research assistant found the location using a combination of online search, Google Earth, and physical maps at a library.

Using the geolocation of markets along with the geolocation of Ayodhya, we calculated the distance as the crow flies each market is from Ayodhya and the average number of customers for that crop market during the period of our analysis. We ran a regression where the dependent variable was the average number of subscribers for a crop market and the independent variable is the distance as the crow flies of that market from Ayodhya. The coefficient on distance from Ayodhya is not significant, effectively ruling out a localized disruption argument.

A second alternative explanation is that traders collude to offer low prices during the ban when farmers don't have the price information. If traders collude in some markets and not in others or if the extent to which farmers are able to collude differs across markets, then prices in some markets would drop by more than others and we would see an increase in price dispersion. Column 2 of Table 3.7 shows that prices were not lower during the text message ban, but were in fact higher during the ban.

A third alternative explanation is that farmers changed their habits. In reaction to the loss of RML price information, the farmers could have changed the crops they are growing to crops with less price dispersion. They could also have made connections in multiple markets to facilitate price collection. Neither of these explanations is reasonable given that the ban lasted only 12 days.

3.4.4 Potential Issues with Identification

The text message ban provides us with a natural experiment leaving little concern for endogeneity in our analysis. However, there are still two potential issues with our identification strategy. First, random fluctuations in price dispersion may coincide with the timing of the ban. To ensure we are not picking up 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 3.7 show the results of regressions for time periods covering August 15, 2010 to November 15, 2010 (an additional one week both before and after the ban) and September 1, 2010 to October 31, 2010 (approximately one week less both before and after the ban), respectively. The coefficients on DuringBan are largely unchanged with the longer and shorter time windows showing that our results are not dependent on the time frame chosen.

It is possible that there are large changes in price dispersion from day to day or week to week. If this is the case we may be capturing a random increase in price dispersion that coincides with the ban. Similar high and low levels of price dispersion could cancel each other out in the pre and post ban periods. One way to check this is to see if two week periods surrounding the ban had levels of price dispersion similar to the two-week period coinciding with the ban. To test this hypothesis, we convert the during ban period to two weeks by including the days just after the text message ban. This ensures that the number of observations and days of week are similar across all two week periods. We then create an additional four two week periods; two before the ban and two after the ban. The results of a regression of $\log(\sigma)$ on dummy variables for each two week period shows that the two week period coinciding with the ban is the highest level of price dispersion. We perform the same analysis with up to five two-week periods before and after the ban as well with similar results. These are removed from the paper to conserve space.

The second concern is that the results are driven by seasonality in price dispersion. If this was the case, then a "ban" in the same time period in 2009 would also exhibit high levels price dispersion. Column 5 of Table 3.7 shows that price dispersion is not significantly higher during the same time frame in 2009. This is in line with Aker and Fafchamps (2010) who find no evidence of seasonality in price dispersion.

3.4.5 Additional Robustness Checks

We perform several additional robustness checks. First, we check if the results are sensitive to the measure of price dispersion using the log of the price range and the coefficient of variation. The price range is the maximum price observed across all markets in a crop state minus the minimum price observed. The coefficient of variation is the standard deviation of prices in a crop market cluster divided by the average price on a day. We also examine whether price dispersion for low prices is higher during the ban. Results from the regressions are in Table 3.8. The coefficient on DuringBan is positive and significant except for the coefficient of variation regressions. This is not surprising since, as noted previously, any effect RML has on prices can potentially cloud the effect RML has on price dispersion.

To rule out the possibility that our results are driven by the choice of our sample, we conduct several robustness checks. We examine the sensitivity of our results to 1) number of observations in a crop market, 2) number of observations in a crop market cluster and 3) number of markets in a crop market cluster. First, we examine whether our results are dependent on the number of observations required for a crop market to be included in our dataset. Table 3.9 shows the results of regressions with

VARIABLES	(1) $\log(P^H_{\max} - P^H_{\min})$	(2) CV^H	(3) $\log(\sigma^L)$	(4) $\log(P^L_{\max} - P^L_{\min})$	(5) CV^L
DuringBan	0.069**	0.011	0.080***	0.095***	0.015*
	(0.027)	(0.008)	(0.031)	(0.027)	(0.008)
PostBan	0.022	0.003	0.025	0.029	0.005
	(0.035)	(0.006)	(0.038)	(0.037)	(0.007)
Observations	14,349	14,349	14,245	14,244	14,349
Day of Week FEs	YES	YES	YES	YES	YES
Adjusted R-Squared	0.883	0.654	0.853	0.887	0.699
Min. No. obs per crop market	10	10	10	10	10
Min. No. markets per cluster	2	2	2	2	2
Min. No. obs per cluster	2	2	2	2	2
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	1671	1671	1670	1670	1671

Table 3.8: Main effect regression results with price dispersion measure robustness. Crop market cluster day panel regressions with two-way error clustering: at the crop level and at the day level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

VARIABLES	(1) log(σ^H)	(2) log(σ^H)	(3) log(σ^H)	(4) log(σ^H)	(5) log(σ^H)	(6) log(σ^H)	(7) log(σ^H)
DuringBan	0.076***	0.072***	0.075***	0.077***	0.077**	0.095***	0.045*
	(0.027)	(0.027)	(0.026)	(0.029)	(0.031)	(0.023)	(0.027)
PostBan	0.024	0.025	0.018	0.033	0.033	0.028	-0.011
	(0.035)	(0.034)	(0.034)	(0.039)	(0.040)	(0.028)	(0.031)
Observations	14,017	14,751	15,150	9,829	9,417	19,741	11,672
Day of Week FEs	YES	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.877	0.871	0.865	0.873	0.875	0.866	0.918
Min. No. obs per crop market	1	20	30	10	10	10	10
Min. No. markets per cluster	2	2	2	2	2	2	3
Min. No. obs per cluster	2	2	2	2	10	1	2
Start Date	23-Aug-10	23-Aug-10	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	8-Nov-10	8-Nov-10
Crop Market Clusters	1689	1579	1467	544	379	6785	1389

Table 3.9: 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. 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

different cutoffs for the number of observations in a crop market that is necessary to be included in the data set. The results are robust to including crop markets with at least 1 (Column 1), 20 (Column 2) or 30 (Column 3) observations.

We examine the sensitivity of our results to the number of crop market cluster observations 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 3.9 shows 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 3.9 shows that the results are robust to using only crop market clusters with at least 10 observations.

Column 6 of Table 3.9 shows that results are unchanged when we include all crop market clusters, even those which occur in the sample once. For this regression, we included a fixed effect for each crop state which controls for the average difference in crop market clusters that occur only once for that crop and state.

Finally, we test whether the results are sensitive to the number of markets in a crop market cluster. Column 7 of Table 3.9 shows that the results are robust to including only crop market clusters with at least 3 markets.

3.4.6 Information and Perishability

It is important to understand which crops benefit from RML price information. Identifying which perishability levels benefit the most from improved information flows will help international aid organizations decide where they should focus their funding. Due to the difficulty in collecting data, research to date on the value of improved informational flows in agricultural supply chains has primarily focused on one or at best two agricultural commodities in a limited number of markets that were chosen to be as homogeneous as possible to reduce concerns regarding correlated omitted variable bias. Therefore, comparisons on how valuable information is depending on operational characteristics such as crop perishability have been limited. The richness of our dataset allows us to investigate these issues.

The perishability level for a crop is time invariant within a crop market cluster.

VARIABLES	(1) $\log(\sigma^H)$
DuringBan_HighPerish	0.097**
	(0.039)
DuringBan_MediumPerish	0.143***
	(0.038)
DuringBan_LowPerish	-0.027
	(0.035)
PostBan	0.026
	(0.035)
Observations	14,349
Day of Week FEs	YES
Adjusted R-Squared	0.877
Min. No. obs per crop market	10
Min. No. markets per cluster	2
Min. No. obs per cluster	2
Start Date	23-Aug-10
End Date	8-Nov-10
Crop Market Clusters	1671

Table 3.10: Perishability regression results. 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

3

Therefore we identify the impact of differing levels of perishability by interacting the perishability variable with DuringBan. Since NumSubscriberBucket is based on percentiles calculated across crop market clusters within a crop as opposed to across all crop market clusters, NumSubscriberBucket and the perishability levels are orthogonal. Note that we do control for the direct effect of perishability through the crop market cluster fixed effects. We therefore estimate

$$\mathrm{PD}_{ckt} = \alpha_{ck} + \beta_1 \mathrm{DuringBan}_t \times \mathrm{Perishability}_c + \beta_3 \mathrm{PostBan}_t + \delta_d + \epsilon_{ckt} \qquad (3.3)$$

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 previously. Perishability levels interacted with the ban are mutually exclusive dummy variables and the coefficient is therefore interpreted as the change in price dispersion relative to the same level of perishability before the ban.

Results of the regression for Model (3.3) are in Table 3.10. It appears that providing price information via a reliable and unbiased third party can provide benefits for crops of high and medium levels of perishability, over and above the impact of reduced price dispersion due to access to mobile phones. Crops with low levels of perishabilty have been shown to not benefit from access to mobile phones. It appears that the availability of reliable information is not the factor keeping these crops from achieving gains from improved technology. Infrastructure or other characteristics may play a bigger role in these crops which are difficult to transport long distances.

3.4.7 Market to market distances in large subscriber crop market clusters

Understanding what, if any, the differences are between crop market clusters with a large number of subscribers and those with a low number of subscribers is managerially important. Observing differences can shed light on the crop market cluster characteristics that provide the biggest benefit to subscribers. Price information services such as RML can use this information to strategically choose crop market clusters that will draw the largest number of subscribers. On the other hand, failure to identify a significant difference between high and low subscriber crop market clusters indicates that as RML continues to diffuse through India, we would expect to observe lower price dispersion, even in crop market clusters where there is currently no observed effect.

An important and observable difference between crop market clusters is the proximity of markets to each other. Markets that are very close to each other may be fairly efficient as information can flow easily between them. However, markets which are very far apart may not benefit from improved information because of the time and money spent transporting goods such a long distance. We therefore devise several measures of market to market distance within a crop market cluster and determine statistically and visually what the differences are between high and low subscriber crop market clusters.

Using the market geolocations described above, we calculate several different measures of market to market distances within a crop market cluster. Figure 3.2 shows an example of distances between markets for a hypothetical crop market cluster. To describe the different distance measures, we use $D_{ij} = D_{ji}$ as notation

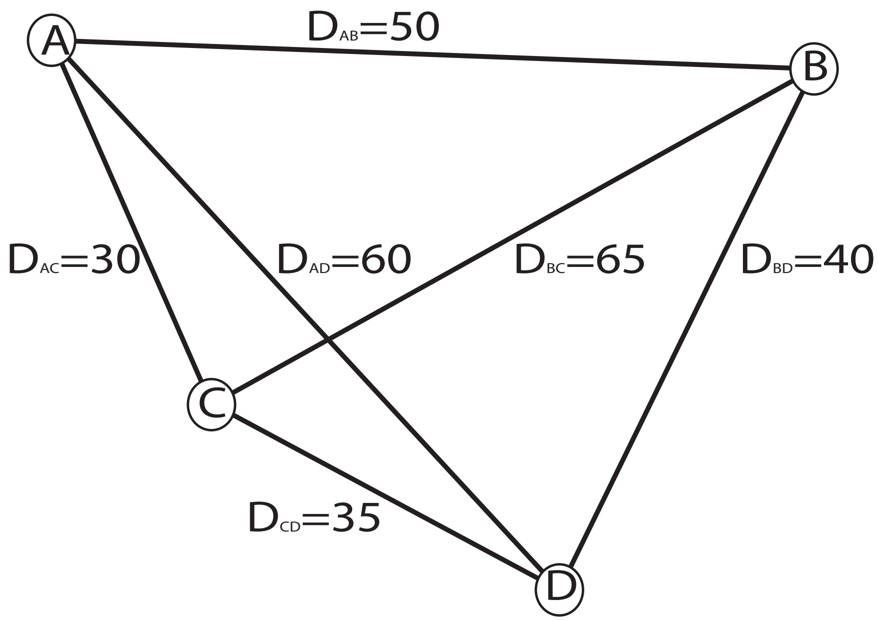

Figure 3.2: Example of distance measures for a crop market cluster.

for the distance as the crow flies between markets i and j. For example, the distance between markets A and B in Figure 3.2 is 50 miles.

The distance between markets measures the extent to which markets within a crop market cluster are close to each other and the extent to which produce can be easily moved between markets. For example, consider a farmer who has arrived at market A. The farmer can either sell at market A for price P_A, or incur a travel cost, τ_{AB}, to travel to market B. Upon arrival at market B the farmer can again sell at market B for price P_B, or incur a travel cost, τ_{BC}, to travel to market C, and so on. Now, with the farmer at market A, they will only incur the travel cost to market B if the expected price in market B is greater than the price at market A plus the travel cost.

We measure this distance in two ways. First, the NearestMarketDistance is the distance between a market and its nearest neighbor in the crop market cluster. Using the example from Figure 3.2, $\text{NearestMarketDistance}_A = \min(D_{AB}, D_{AC}, D_{AD}) = \min(50, 30, 60) = 30$. Similarly for markets B, C and D the NearestMarketDistance is 40, 30 and 35, respectively. We calculate the mean, median and standard deviation of this distribution of distances. Continuing with the example from Fig-

	Kolmogorov-Smirnov
AverageNearestMarketDistance	0.336
MedianNearestMarketDistance	0.034
StDevNearestMarketDistance	0.001
AverageMarketDistance	0.003
MedianMarketDistance	0.054
StDevMarketDistance	0.048

Table 3.11: Differences in high and low number of customer crop market clusters. 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.

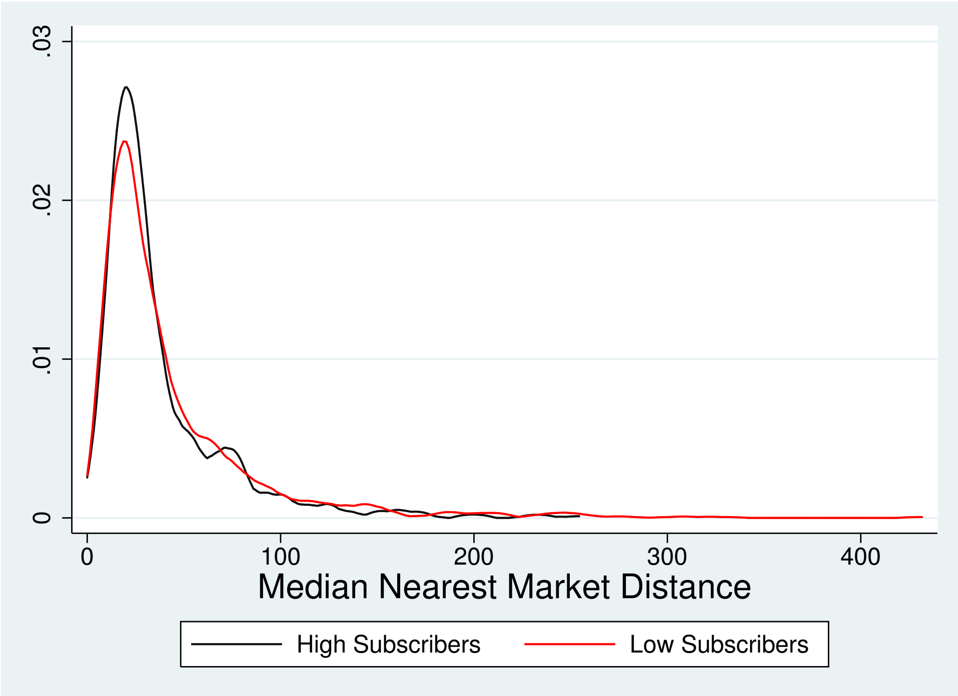

Figure 3.3: Distribution of median nearest market distance for high and low number of subscriber crop market clusters.

ure 3.2, the distribution of NearestMarketDistances is $\{30, 40, 30, 35\}$ which means AverageNearestMarketDistance $= 33.75$, MedianNearestMarketDistance $= 32.5$, and StandardDeviationNearestMarketDistance $= 4.79$.

The second distance measure, MarketDistance, looks at all of the market to market distances, not just the nearest market distance. This translates into all of the edges in the graph. In Figure 3.2, this would correspond to $\{D_{AB}, D_{AC}, D_{AD}, D_{BC}, D_{BD}, D_{CD}\}$ or $\{50, 30, 60, 65, 40, 35\}$. As before, we calculate the mean, median and standard deviation of this distribution of distances. Calculations for the hypothetical example in Figure 3.2 are: AverageMarketDistance $= 46.67$, MedianMarketDistance $= 45$, and StandardDeviationMarketDistance $= 12.02$.

Table 3.11 shows the p-values for Kolmogorov-Smirnov tests of the equality of distributions of each distance metric across high and low number of subscriber crop market clusters. The results show that there is a significant difference in the distribution of market to market distance metrics between high and low number of subscriber crop market clusters. Figure 3.3 shows the kernel density distribution of the median of NearestMarketDistance for high and low number of subscriber markets. From the figure we can see that there are no crop market clusters with a low number of subscribers for median nearest market distances of above 300 miles. However, low number of subscriber crop market clusters have a median distance of greater than 400 miles in some cases. Providers of a price information service, such as RML, should take this into consideration when deciding where to offer the service. International aid agencies can also use this information to decide which groups of markets to offer subsidies for.

3.5 Conclusions

Mobile phones are rapidly changing supply chains in developing economies through improved information flows. Previous research has verified that access to mobile phones 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, reliable and unbiased price information delivered via text message impacts geographic price dispersion. Utilizing a detailed, market level dataset from Reuters Market Light (RML), we exploit a natural experiment, where bulk text messages were unexpectedly banned for 12 days across India. Our results show that the average spatial price dispersion of 170 crops across 13 states increased by 7.6% (95% C.I. of 2.3 to 12.8%) 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 and results are similar for multiple measures of price dispersion. We explore several alternative explanations, and issues of misspecifcation and spurious regression but find no reason to doubt our results. Furthermore, with 170 crops and 64 days in our analysis, we can estimate extremely flexible error structures that are robust to arbitrary autocorrelation and heteroskedasticity within crops as well as correlation across crops on a given day. We are confident that errors are not underestimated.

Importantly, the highest price dispersion during the ban is recorded in markets where RML has the largest number of subscribers. It appears there is a penetration level at which providing regular, reliable and unbiased price information can influence geographic price dispersion. Unfortunately, detailed data on the number of farmers in each state for each crop was not complete enough to determine the precise penetration level needed. However, RML executives we have spoken with estimate the penetration of this service to be as low as 2% percent in many markets, suggesting that the RML information service has an effect at very low levels of penetration. Furthermore, measures of market concentration for groups of markets that have a high number of subscribers versus groups of markets that have a low number of subscribers are significantly different. The findings suggest that subscribers value information for some groups of markets more than others.

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. Non-perishable crops do not benefit from the information service. It is possible that access to mobile phones have made markets for these crops fairly efficient already or that information is not the barrier to market efficiency, but reliable infrastructure for transporting these typically heavy crops. Future research should attempt to disentangle the two effects.

Our research contributes to the academic literature on how information and communication technologies impact rural supply chains in the developing world. We show that improvements in such technologies are not by themselves sufficient to ensure access to the best information. Organizations that utilize the ICT infrastructure to provide reliable, unbiased and up-to-date information can further contribute to reducing price dispersion. Our research also throws light on how such

ICT applications affect crops with different levels of perishability.

Our results have important managerial and policy implications, providing specific advice on which types of crops would stand to benefit the most by being covered by such a service. On the managerial side, it provides support for the business model of third party information providers, such as RML, by showing that they do make a difference in the functioning of agricultural crop markets in the developing world. Furthermore, firms offering a price information service should focus their operational and marketing efforts on crops with high and medium levels of perishability.

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 can be a cost effective way to reduce inefficiencies. Furthermore, due to farmers sharing the service, for-profit companies may under-provide these types of services because they cannot reap the entire benefit of doing so. Ayres and Levitt (1998) reach a similar conclusion when examining the impact of Lo-jack, an unobservable automobile security device, on crime rates. The significant positive externalities of installing Lo-jack in a single car far outweigh the benefit to the individual and subsidies of the service would be social welfare improving. Subsidizing the RML service may increase the proliferation of these types of information aggregation and dissemination services.

Our methodological contribution is 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 can identify areas where existing technological infrastructure can be leveraged to improve market and operational functioning. Researchers in information systems and operations management should embrace the natural experiment econometric methodology whenever possible to investigate these issues.

Although our fertile data set and natural experiment econometric specification have allowed for a robust investigation of the value of reliable and unbiased 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 true 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. However, this could also be beneficial since farmers could have changed the way they gather information during a longer disruption. 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 - how prices within a market move from day to day. Finally, using the crop market cluster day unit of analysis has complicated any analysis of distances. The seemingly limitless ways in which one can calculate a distance measure for a group of markets each have their drawbacks. Future research can address this through an alternative econometric specification.

CHAPTER

4

DEVELOPING ELECTRONIC MARKETS IN LOW-TECH ENVIRONMENTS: INDIA'S AGRICULTURE MARKETS

4.1 Introduction

A deep stream of information systems (IS) research emphasizes the role that technology plays in creating more accessible markets, increasing efficiency, and improving outcomes for participants (Bakos, 1997; Malone et al., 1987). However, this research has largely focused on business-to-business (B2B) and business-to-consumer (B2C) applications in developed countries where technology is already prevalent among market participants. Empirical studies have examined, among other settings, simultaneous online and in-person auctions for used cars (Overby and Forman, 2011; Overby and Jap, 2009), the difference between price dispersion for books and CDs in physical and internet sales channels (Brynjolfsson and Smith, 2000), the use of shopbots or internet computerized real-time price comparison algorithms on book prices (Tang et al., 2010), and transaction prices in high volume government procurement (Ghose and Yao, 2011).

Less well understood is how markets can utilize information technology (IT) to enhance market efficiency when participants use minimal IT in their own operations, and market processes are entirely manual. In this paper, we aim to answer the following questions: In an environment with minimal IT, can the implementation of a price and market support information system enable markets to operate more efficiently? Can a relatively small-scale investment in creating a partially electronic market deliver benefits similar to what has been achieved in fully electronic markets? Finally, we introduce videos and photos of current market practices and the new IS in the market to familiarize the reader with the context and to enhance the impact of our research.

Agricultural markets in developing economies provide a diverse context in which to answer these questions. Even low-end IT (by developed world standards) can inform market participants and reduce the leverage of intermediaries, to the benefit of farmers and end consumers. While experimentation with the use of innovative market technology has been prevalent in Dutch flower auctions and trading of futures contracts at the Chicago Mercantile Exchange (Clemons and Weber, 1991; van Heck et al., 1995), only recently has it been put to use in smaller scale markets and in emerging economies. We evaluate the role IT has played in making fragmented agricultural markets in developing economies more transparent and efficient. The results show that providing market participants with price information via daily text messages can significantly reduce geographic price dispersion.

Observing markets and market participants is an integral step to understanding how IT contributes to the way these markets operate. Only through study of market participants and operations will we be able to answer research questions about

ITs contribution to agriculture markets. For this reason, one of the authors spent 11 weeks in India gaining hands-on, in-depth knowledge of the markets through repeated interaction with market participants all along the supply chain and with government agents, who are charged with enforcing regulatory rules, developing plans for market committees, and advising/supervising marketing committees in endeavors necessary to improve the functioning of agriculture produce markets. Understanding the use of technology in communicating price and volume information to market participants, as well as best practices and other relevant information, was the focus of these discussions. In an attempt to provide the reader with some of the contextual knowledge gained through the field research, we provide links to nine videos throughout the paper. The reader is encouraged to view each video as if it were contained within the paper itself.

4.2 India's Agriculture: Markets Structures in Use

The Indian food crop markets illustrate the consequences of costly search and minimal price information. Farmers face high price uncertainty, and low supply chain coordination leads to significant waste. Moreover, large travel distances coupled with poor road quality make it difficult for market participants to respond to the limited market information that has been available. This reduces growers bargaining power when entering the market. The result is that farmers in India earn as little 30 percent of the value of the final price of their raw produce versus 50 percent in the United States (World Bank, 2008). According to the 2001 Census of India there are 235 million individuals involved in agriculture (23% of total population) of which 128 million are cultivators. In 2003, crops were sold in 7,360 regulated and 27,294 unregulated markets. Even a slight improvement in efficiency will have a drastic effect on welfare, given the scale of the agricultural sector.

Almost all states within India are regulated according to the national governments Agricultural Produce Marketing (APM) Act. The APM Act enables the state

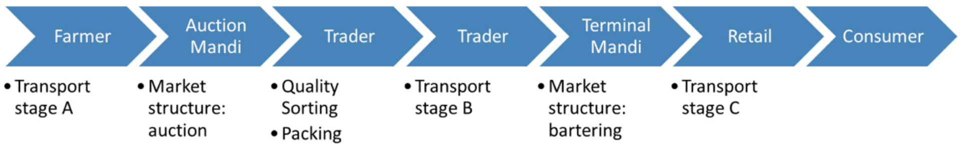

Figure 4.1: High-level overview of flow of goods through the Indian agricultural market. Source: Parker et al. (2012)

Figure 4.2: Farmer transporting onions to the Lasalgaon, Maharashtra auction mandi.

to regulate spot markets, called mandis, which operate under the direction of Agricultural Produce Marketing Committees (APMCs). An APMCs primary functions are establishing and managing mandis, and managing the licensing of traders within these mandis.

Figure 4.1 shows an overview of the path produce takes once a farmer harvests the crop. Smaller farmers may face an additional intermediary who purchases the produce at the farmers field, offering a farm gate price. This intermediary aggregates produce from many small farmers for transportation to, and selling at, the mandi. Another trader could also buy produce at one terminal mandi, such as Pune, and transport it for sale at another terminal mandi, such as Mumbai. Finally, there could be an intermediary who purchases goods at the terminal mandi, breaks bulk, and sells to retail shops. The end result is that there are six to eight intermediaries between the farmer and the consumer in the Indian agriculture market versus two to three in the United States (World Bank, 2008).

Figure 4.3: Farmers auction slip at the Pimpalgaon, Maharashtra mandi.

Figure 4.2 shows the first step: a truck en route to an auction mandi. In this picture, onions are being transported to the Lasalgaon, Maharashtra, auction mandi. A truck of this size holds approximately 10 quintals (1,000 kgs or 2,200 lbs) of onions. There are two types of auction mandis in India: APMC-facilitated and commission agent-facilitated.

In APMC-facilitated auction mandis, farmers sell to traders. The APMC facilitates exchange by providing an auctioneer, overseeing auctions, weighing produce, coordinating payment and produce delivery, and resolving disputes. In these mandis, farmers bring their produce to the mandis physical location. They are assigned a number upon arrival and wait in the parking spot assigned to that number. Once the market opens, the APMC-provided auctioneer and administrator lead 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 auction, or English auction. Once the auctioneer finalizes the bidding process, the farmer has the opportunity to refuse or accept the per quintal, kilo or bushel price. The produce is either sold in its entirety, or not at all. If the offer is refused the farmer can choose to take his produce to a different mandi, or home to return to the same or a different mandi on another day.[1] If the offer is accepted, the auctioneers assistant records the price and hands a sheet of paper with the price information to both the farmer and the trader. Figure 4.3 shows an example of this sheet of paper for onions auctioned at the Pimpalgaon, Maharashtra mandi. The farmer takes the produce to the weighing station where the exact weight of the produce is measured. The trader later pays the farmer according to the price set in the auction and, in regulated markets, pays a 1-2 percent fee to the APMC for facilitating the auction and providing a physical location for the auction.

A video of onions being auctioned at the Lasalgaon, Maharashtra mandi, filmed by one of the authors, is available at:

- `http://www.youtube.com/watch?v=s6ibXa4gZ-g`

Lasalgaon is a major mandi for onion in India. The video begins by showing the auctioneer, the farmer and some of the traders. We then follow the market participants from truck to truck in a series of auctions. Auction durations are short, so a brief notification announcing the end of the auction is displayed for the viewer. At the very end of the video we see a glimpse of the auctioneers assistant. A second video shows a more relaxed, but similarly structured mandi in Pimpalgaon, Maharashtra:

- `http://www.youtube.com/watch?v=hzYKCgacv0Y`

A commission agent-facilitated auction mandi is similar to an APMC-facilitated auction mandi in that goods are brought to the mandi by the farmer and then an open outcry, ascending first price auction is used to obtain a per quintal, kilo or bushel price. However, in these mandis commission agents rent space and perform the auctions. Upon arrival, a farmer approaches an agent who assumes control of the goods.

The commission agent leads traders around to the produce performing the auctioning duties that APMC officials perform in APMC-facilitated auction mandis. The farmer can again reject the auction price and take the produce home or to another mandi. If the farmer accepts, the auctioneers assistant records the price

[1]While this is an option for farmers, it does not occur often.

Figure 4.4: Commission agents stall at the Nashik, Maharashtra mandi.

handing a sheet of paper with price information to both the farmer and the trader. The commission agents workers then calculate the exact weight of the produce. The purchasing trader pays for the produce at the commission agents stall where the farmer also collects their payment net the fees for facilitating the auction (close to 7 percent of the selling price at the Nashik, Maharashtra mandi) and weighing the produce. In addition to the cost for renting the stall, commission agents in regulated markets must also pay a one to two percent fee to the APMC. Many commission agents have a computer database of every single transaction that goes through their stall. Figure 4.4 shows one such stall at the Nashik, Maharashtra mandi.

Videos of produce being auctioned at a commission agent-facilitated auction mandi in Nashik, Maharashtra are available here:

- Fenugreek: `http://www.youtube.com/watch?v=TjCoxJEuozo`
- Green onion: `http://www.youtube.com/watch?v=cfb4eebkDPE`
- Carrot: `http://www.youtube.com/watch?v=VhQkBha1CgE`

Farmers and traders do not exhibit a strong preference for APMC auction mandis over commission agent auction mandis. State government officials select one or the other structure for their regulated mandis, and certain regions appear to select one structure while other regions favor the other.

Figure 4.5: Tomatoes prepared for shipping from Pimpalgaon to a terminal mandi.

After produce is purchased by a trader in an auction mandi, it is sorted according to quality and prepared for shipping to either domestic or international markets. Videos of onions being sorted and packaged for transportation in Lasalgaon and tomatoes being packaged for transportation in Nashik are here:

- Onions in Lasalgaon: `http://www.youtube.com/watch?v=qFKo3AqmeQU`
- Tomatoes in Nashik: `http://www.youtube.com/watch?v=oRr2j30CKSo`

The auction purchasing trader then transfers the goods to a second trader who oversees transportation from the auction market to the port for export produce or to the domestic produce wholesale markets, called terminal mandis. Figure 4.5 shows tomatoes readied for transportation from Pimpalgaon, Maharashtra to a terminal mandi. The transporting trader has rented a stall in the terminal mandi where the produce is sold to retailers and some large end consumers. Unlike the other two market types there are no auctions for the produce in terminal mandis. The trader sets a price and the retailers and consumers visit different trader stalls to purchase goods of varying price and quality. As is typical throughout India, the main pricing mechanism in terminal mandis is bartering. Figure 4.6 shows the Pune, Maharashtra terminal mandi.

Figure 4.6: Pune, Maharashtra terminal mandi.

4.3 Enhancing Market Structures with IT

Research studies demonstrate that IT can improve how markets operate. However, the agriculture sector in India is not well-equipped, and has not proven itself interested in launching market price dissemination systems.

4.3.1 Early Price Dissemination

With approximately 7,360 regulated mandis and 27,294 rural unregulated mandis of all three types throughout India as of 2003, obtaining price information for even a single crop in a single state can be daunting for market participants (World Bank, 2008). Before the use of IT in the Indian agriculture market, the only option for market participants to gather valuable mandi price information was to physically travel there. This is costly in terms of both time and money. This is especially true in India where inter-mandi distances are substantial as shown in Figure 4.7.

The large distances between markets, poor road quality, and points of heavy traffic create a fragile transport infrastructure for market participants. As a result, discovering price information is a regular and important task for market participants. One farmer we interviewed at the Lasalgaon, Maharashtra mandi reported making 20 trips to the market every year, driving approximately 75 kms (45 miles) each

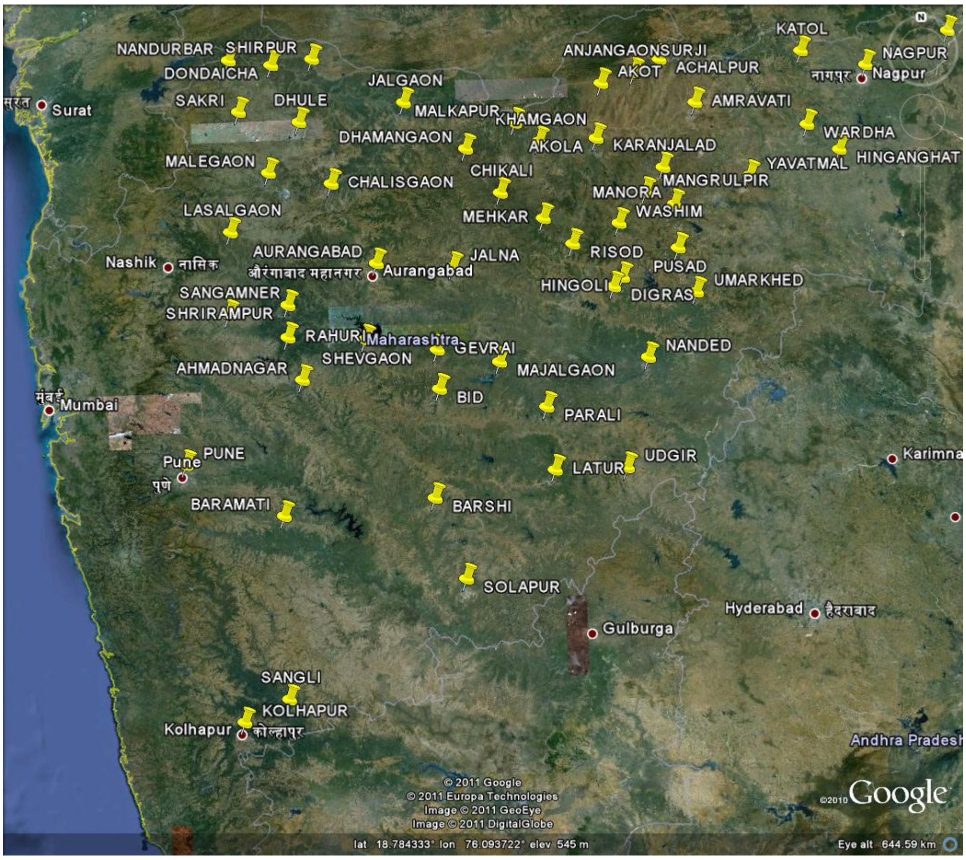

Figure 4.7: Wheat mandis in Maharashtra region. Mandis are geographically dispersed leading to inefficiencies in the market. The distance from Pune to Lasalgaon is approximately 140 miles.

	Wired Phone	Cell Phone	Internet
Urban	26.10	525.17	*
Rural	8.76	266.21	*
Total	34.87	791.38	61.34

Table 4.1: Number of subscribers (in millions) for wired and cell phones in India as of February 28, 2011 and estimated access to internet in 2009. Asterisks indicate that the allocation of internet access into urban and rural is currently unknown.

way. Because of the difficulties in determining market prices elsewhere and transport costs, this farmer always sells in the Lasalgaon, Maharashtra mandi.

Landline-wired telephony in India gave some market participants the option of calling the mandis directly. However, landline telephony never became prevalent. Table 4.1 shows subscription levels for phones and the internet.[2] Wired phone penetration levels have only managed to reach 35 million subscribers. Of these subscribers only 8.8 million are in rural areas where market participants predominantly

[2]Phone data from Telecom Regulatory Authority of India Press Release No. 29/2011 downloaded on April 18, 2011 from: `http://www.trai.gov.in/WriteReadData/trai/upload/PressReleases/816/Press_release_feb%20-11.pdf`. Internet data from International Telecommunications Union downloaded on April 18, 2011 from: `http://www.itu.int/ITU-D/ICTEYE/Indicators/Indicators.aspx`.

live. With the population at 1.2 billion as of the 2011 Census, total penetration levels of wired phones are nearly 3 percent.[3] At these low penetration levels, direct-to-mandi calls were not seen to have affected prices in markets.

4.3.2 User Devices

Mobile phones arrived in the 1990s, and penetration is now far higher than wired phones at close to 66 percent of the population. The mobile phone has the added benefit of checking prices while transporting goods to the market. For example, consider a farmer whose farm is equidistant from two markets. Traveling to either market entails first driving down a long road, which comes to an intersection with market A down the road to the left and market B down the road to the right. With a wired phone the farmer must choose before leaving home which of the markets he or she will visit. For argument sake, say the farmer chooses market A, which has the higher price. However by the time the farmer gets to market A, the price at market B is higher. The farmer sells the produce at the lower price in market A, and will be disappointed to learn market B had a higher price. With a cell phone in hand the farmer can wait until they reach the intersection before calling the markets to find out indicative prices thereby partially reducing the timing risk they face.

The scenario described above is precisely what occurred in fish mandis with the introduction of cell phone service throughout the Indian state of Kerala (Jensen, 2007). Observing prices before and after cell phone introduction, Jensen finds that fisherman use the cell phones for price discovery and better choice of market to go to. In doing so, they shift supply and demand resulting in a near elimination of waste and an increase in producer welfare.

The impact of mobile phone service on markets has also been observed in grain markets in Niger (Aker, 2008b). In this setting cell phone service was gradually phased in throughout Niger in a manner similar to Jensen (2007). The findings suggest a decrease in price dispersion across markets of at least 6.4 percent, and a more efficient outcome. Introduction of cell phones may also have lessened the

[3]Population estimates from the 2011 Census of India downloaded on April 18, 2011 from: `http://www.censusindia.gov.in/2011-prov-results/data_files/Figures_At_Glance.pdf`

impact of the 2005 food crisis.

The Ministry of Agriculture began to provide market participants with daily price data in 2001 as the result of its introduction of the `http://agmarknet.nic.in` website. However, internet access penetration levels are low throughout India reaching only 5 percent (See Table 4.1). Moreover, the website only collects and disseminates price and volume information for regulated mandis. In Maharashtra alone, there are over 2,700 unregulated mandis compared to 295 regulated main mandis and regulated 609 sub mandis (World Bank, 2008).

The authors could not identify research or measures of the impact the agmarknet website on market prices. However, two research papers based on new options for market participants in India showed that coordination benefits provided by IT are not limited to cell phone usage. Electronic auctions are reducing the advantage that intermediaries had over the farmers in the Indian coffee market. When compared to mandi auction prices, the electronic auctions result in four percent higher prices (Banker and Mitra, 2005, 2007). Internet kiosks providing farmers with price information and hubs with better quality detection measures have been introduced into the India soybean market (Goyal, 2010). The result is an increase in the wholesale price of soybeans as well as evidence of an increase in the cultivated area used for soybeans. While intermediaries are negatively impacted by internet kiosk introduction, this is offset by a large gain for farmers, resulting in a net welfare gain.

In areas where IT is even less prevalent than in India, radio is being put to use for agricultural market price dissemination. Ugandan maize market prices are collected and broadcasted weekly over the radio, impacting the farm-gate prices that farmers receive (Svensson and Yanagizawa, 2009). Families with radios and in areas where the service is offered received 15 percent higher prices for their produce.

4.4 Reuters Market Light

The unique challenges and business opportunities associated with providing timely and accurate pricing information to Indian agricultural market participants did not go unnoticed. In October 2007, Thomson Reuters introduced a text message (SMS) based information service to market participants in India called Reuters Market Light (RML). The service was conceived in 2005 when a proposal was brought to the attention of a Reuters Vice President by the head of the Reuters Innovation Program. The project took off with a small investment to fund a feasibility survey. By early 2006, the team had identified the demand for market information that they had anticipated. Prototyping of the service began in Maharashtra in April 2006 with sourcing of information and collection of the appropriate rights to disseminate the data. By August 2006, the team was ready to pilot the service, which lasted through January 2007. Tweaking of the selling and distribution of the service was performed throughout the pilot and into February 2007.

On April 23, 2007 a trial was launched in Maharashtra. In October 2007, RML ended the trial stage and officially launched with close to 5,500 paying customers for 5 crops. The service took off after the launch covering over 250 crops in 1,000 mandis across 13 states in India at the time of this writing. Although generating a relatively small proportion of the companys revenues, RML has a high profile.

- The Chief Executive of Thomson Reuters, Tom Glocer, is a champion of RML and discusses the importance of RML in establishing a transparent and efficient agriculture market in India here: `http://www.youtube.com/watch?v=PbFfpb3K91Q`.

- A more recent video with Amit Mehra, RML Managing Director, and Maanav Yashroy, RML Vice President of Sales and Distribution, touches on RMLs importance in market making and discusses the way in which market participants are connected to the service: `http://www.youtube.com/watch?v=IHCi02kYauM`.

As Mehra and Yashroy mention in the video, the subscription process is simplified for market participants. They go to a local agricultural store where they purchase a scratch card that entitles them to a 3, 6, or 12 month subscription costing approximately Rs. 80 ($2) per month. The market participant then chooses two crops and up to three mandis for each crop, a taluka (similar to a U.S. county) for which they would like weather forecasts, and one of nine languages in which they can have

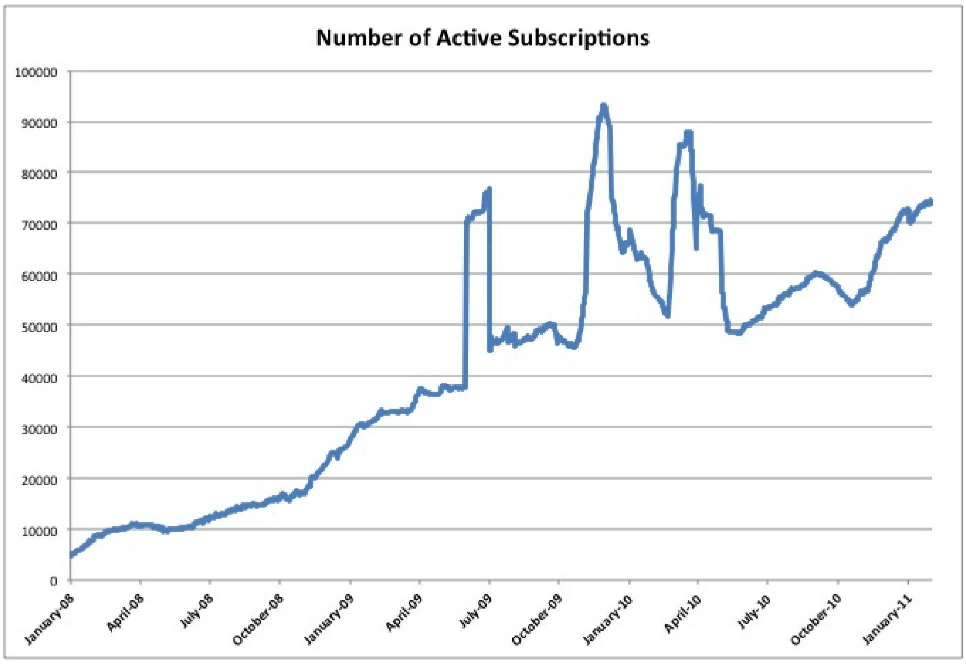

Figure 4.8: Number of active subscriptions from January 1, 2008 to January 31, 2011. The three spikes correspond to different marketing strategies enacted by RML.

the text message delivered: Bengali, English, Gujarati, Hindi, Kannada, Marathi, Punjabi, Tamil and Telugu. They place a phone call to the RML call center where the code on the scratch card is validated and the subscribers choices are recorded in the RML database. The subscriber begins receiving RML text messages within two days.

The ease with which a farmer can obtain a subscription helped RML gain a large number of users. Figure 4.8 shows the number of active RML subscriptions from January 1, 2008 to January 31, 2011. In just more than three years, RML has grown their subscriber base from close to 5,000 to nearly 75,000. Three strategic marketing strategies (such as offering a free one month subscription with the purchase of an oil machine for certain farm machines) helped to push (temporarily) the number of subscriptions to a peak of just over 93,000 at the end of November 2009.

Text messages are sent to the subscriber daily containing price and volume information for the crops and corresponding mandis of their choice as well as local weather forecasts. In addition they receive local and national news alerts, such as when weather in another country may impact prices of their crops, and crop-specific advisory such as tips on irrigating their crops, the amount and type of fertilizer to use, when/how deep to plant their seeds, and when to harvest their crops for improved quality and yields. All text messages are in the subscribers chosen language.

Collecting the price information is not a simple task for RML. A market reporter (MR), employed by RML, visits each mandi every day to observe prices and volumes. The MR verifies that the prices and volumes they have observed are representative of the days prices by visiting with mandi officials. Once the prices and volumes have been verified the MR submits a short text, which is automatically recognized by the RML database. An algorithm checks the prices for validity and flags any potential errors. A chief market reporter (CMR), an RML employee who oversees market reporters for several mandis, is notified of these potential errors. They first check the data that was submitted and compare it to the previous days prices. Then the CMR contacts the MR to verify the information and any specific reasons for the drastic price or volume changes. The CMR can modify the prices or approve the prices before they are disseminated to the subscribers via text message. Figure 4.9 shows a sample text message from October 27, 2010. The message shows prices and volumes for soybean in three mandis.

Dissemination of the weather, news and crop advisory messages is identical to the price information but with different methods of sourcing and verifying the data. Weather data is sourced from an independent Indian weather forecasting team. Figure 4.10 shows a sample weather forecast message for Pune, Maharashtra.

4.5 The RML Effect

Much of the evidence on the benefits of RML is anecdotal. However, the impact of price information in informing farmers of where to sell can be measured directly. Jensen (2007) develops a model in which farmers strategically decide where to sell their produce. Shifting supply from a low price market to a high price market results in a net welfare gain. If farmers take advantage of inter-market deviations from the law of one price in this way, price dispersion between these markets will decrease. Chapter 3 showed that RML is reducing geographic price dispersion by as much as 7.6 percent. The results are applicable across a wide range of crops and in

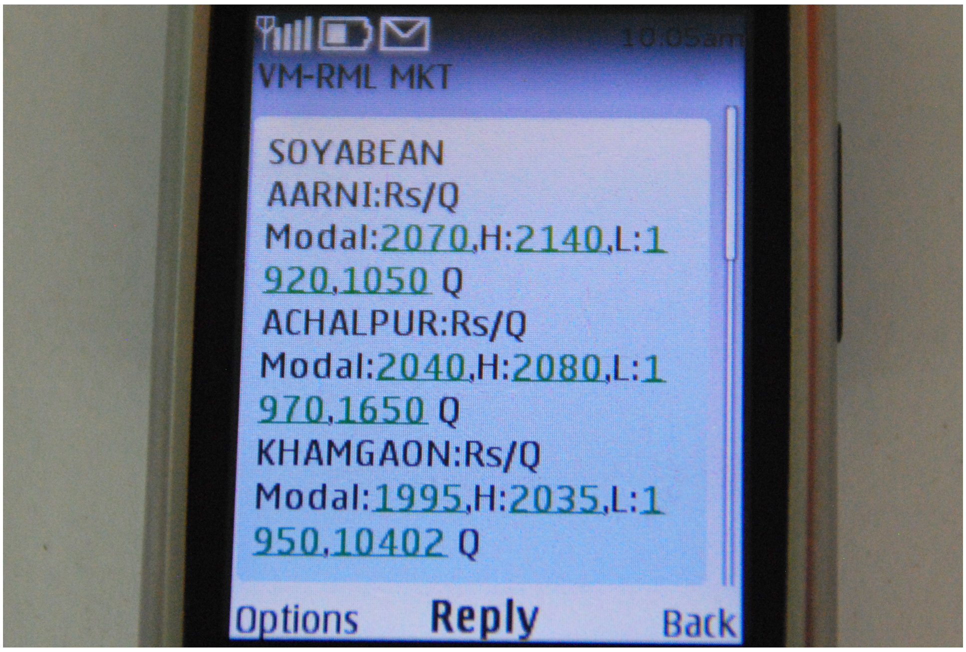

Figure 4.9: Sample price information text message. Prices are per quintal (100 kgs or 220 lbs) for soybean in three mandis: Aarni, Achalpur, and Khamgaon. Modal is the price that was achieved most frequently for auctions, H is the highest price received and L is the lowest price received. Q is the total quantity traded throughout the day.

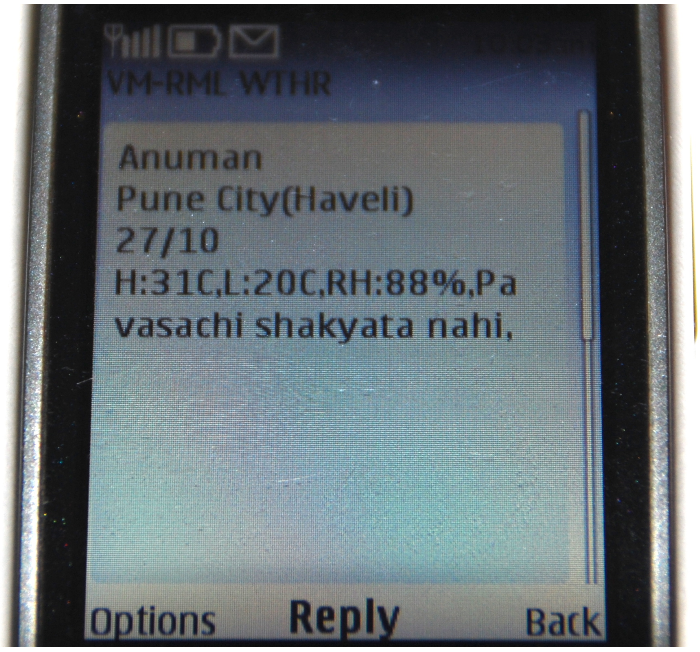

Figure 4.10: Sample weather forecast text message. The message corresponds to Pune, Maharashtra on October 27, 2010. High and low price forecasts are given in degrees centigrade. RH is the residual humidity and the final statement in Marathi translates to "no chance of rain."

Greater price dispersion	27	9.1%
Insignificant change	34	49.3%
Lower price dispersion	8	11.6%
Total	69	100.0%

Table 4.2: Change in standard deviation of crop prices for 69 crops across markets when RML was shut down compared to when RML was operating. Greater and lesser price dispersion are measured at a 5% significance level.

all states in which RML is currently providing price information. Importantly, the reduction in price dispersion is highest in areas where RML has a relatively large number of customers. Furthermore, RML is shown to differentially impact crops with varying levels of perishability.

A nationwide ban on bulk text messaging in India, which shot off the data provided by RML, provided a measure of the value of RMLs market information. The ban was completely unexpected and was put in place to prevent technologically coordinated riots due to a controversial high court verdict. Without the RML price information sent to their phones every day, farmers were forced to gather price information the old way by calling or visiting markets directly or asking neighbors or traders for the prices in nearby markets.

In our analysis, we calculated the daily standard deviation in prices across markets for crops with markets open before, during and after the bulk text message ban. We then tested whether the standard deviation of prices across markets for the same crop was higher during the 12-day ban when price information was not as readily available as before and after the ban when RML subscribers received the price information daily. In 27 out of 69 crops (almost 40%), price dispersion is significantly higher during the bulk text message ban than before and after the ban using a 5% significance level.

4.5.1 Effects on Farmers

While Chapter 3 and the previous analysis look at how RML has impacted overall efficiency of the entire agricultural market, there are numerous benefits to the individual farmers who subscribe. These benefits include improved decision making on when to sell their produce, an increase in bargaining power, improved crop quality and yields, improved production decisions, and help in deciding which crops to cultivate.

- **Timing of sale for less perishable crops** - For farmers who have the financial flexibility to delay the receipt of revenues for their crop, RML is providing information that helps the farmer decide when to sell. Some farmers now store their produce and wait for potentially higher prices instead of taking it to market immediately after harvest (Mittal et al., 2010). Providing the farmers with daily prices allows them to track trends in the market which they can take advantage of. The text messages on national and international news also help farmers decide when to sell. If they know a hurricane or frost has destroyed much of the orange crop in Florida or Spain, the farmer can wait until global markets react, and receive, for instance, higher prices for their oranges in the mandis.

- **Better negotiating leverage** - Farmers can use the price data for increased bargaining power. Knowing the prices that are charged in the terminal market allows the farmer to negotiate a higher price for their produce, thereby reducing intermediary margins. If the farmer has a higher marginal value of money than the intermediary, then this wealth transfer will result in a net welfare improvement.

- **Improved harvesting decisions** - Weather information also leads to improved crop quality, yields and a reduction in waste. For example, if fertilization is followed shortly by rainfall, the fertilizer will be washed away and wasted. Knowing the weather also helps with timing harvesting. Crops that have been harvested but not brought to the mandi can be exposed to severe rains, which can damage the crop. Some estimates put these post-harvest loses at 10 to 35 percent of revenue (Mittal et al., 2010).

- **Better crop planting decisions** - Crop advisory information supplied to the farmers allows them to maximize the chance of high quality produce from the sowing season through to post harvest. The advisory tells them when and how deep to plant their crops, how much water to provide and when optimal harvest times are. Further anecdotal evidence is that "by taking immediate action on receiving an SMS on the relative humidity, [a farmer] protected his crops while another farmer in his vicinity lost Rs. 500,000 [$12,000]."[4]

- **Insight into unusual demand conditions** - Farmers can also use the volume information to modify their production. In one example, knowing the demand for flowers in the local market, farmers have begun bringing more flowers to the market and realizing higher profits on days with large demand (Mittal et al., 2010).

- **Improved profitability** - Finally, farmers are taking advantage of decreased price uncertainty to branch into more profitable crops. Switching to a new crop can be risky if prices are volatile relative to the crop that a farmer currently produces. Some farmers are using the crop advisory messages to learn best practices other crops as well. The knowledge allows them to confidently and successfully diversify their production and realize increased revenues from higher margin crops such as roses (Mittal et al., 2010).

4.5.2 Effects on Traders

Inevitably, many of the above benefits to farmers come at the expense of traders. A decrease in relative bargaining power means that aggregating intermediaries provide small farmers with higher farm gate prices. Prices in markets are less dispersed, which means reduced market arbitrage opportunities. These combine to reduce intermediary profits.

On the other hand, traders can also share in the benefit of increased price transparency (avoid overpaying), higher quality produce, and higher yields. Reduced price uncertainty simplifies revenue management for the trader. Higher quality results in less produce lost to spoilage en route to terminal or international markets with higher prices. Higher yields can allow traders to invest in larger transport vehicles, possibly reducing per kilogram transportation costs. Finally, with higher

[4] `http://bit.ly/9rjhjg`

quality and volume of produce flowing through mandis, the APMC will collect more revenue that will be used to improve storage facilities at mandis, further reducing post-sorting waste.

Theoretical reasons based on search and reduced uncertainty, and anecdotal evidence from RML users and management team, indicate the service is raising farmer welfare, but reducing trader profitability. However, data and statistical evidence are scarce at present. Our current analysis does not allow us to distinguish between quantifiable net benefits to farmers and traders, only to the overall efficiency of the agriculture market. Evidence from financial market computerization suggests transparency compresses intermediaries profit margins, but increases the volume of market activity. In some cases, IT has proven beneficial to intermediary-traders that adapt to the new market conditions. Future research will address whether agricultural traders in India have realized benefits to offset the reduction in their informational advantage.

4.6 Conclusion

In this paper, we have demonstrated the importance of technology-supported price dissemination in making markets more efficient. Using agriculture as a backdrop, we have studied how an existing technology can be used to create more efficient markets. Recent research has highlighted how IT can be used to help coordinate supply and demand leading to less price uncertainty and more efficient agricultural markets in developing economies. The introduction of mobile phones, internet kiosks and electronic auctions has helped to reduce the power of intermediaries in agricultural markets giving more power to the farmer.

Reuters Market Light (RML) is a text message based subscription information system that provides farmers with personalized information pertaining to their crops in their area. Compared to market systems in use in more developed economies, it is a simple IT platform. An empirical analysis of markets and crops in which RML operates finds that inter-market price dispersion is decreased as a result of the price information provided by RML. Such price convergence has been found to lead to welfare benefits. In addition, survey and anecdotal evidence indicates that the increase in information has helped farmers to decide when to sell their produce, an increase in bargaining power, improved crop quality and yields, improved production decisions, and help in deciding which crops to cultivate.

RMLs launch provides an example where a relatively small amount of IT capital investment can provide partial e-market capabilities and benefits to developing economies. IS researchers should leverage their unique skill sets to identify other environments in which partially electronic markets can operate in a manner similar to fully electronic markets. With RML and other competing services being introduced into developing economies, there are numerous opportunities for empirical research.

We find evidence, and document it with video and pictures, that RML has made Indias regional agriculture mandis more efficient. RML has empowered farmers who can avoid markets with inferior prices. and who grow crops more productively and profitably. The implication for e-markets research is that a low-tech infrastructure can nevertheless support a highly targeted price information system. Key factors are a reliable information gathering mechanism, standardization (in this case) on low-end mobile phones, customizable yet succinct messages (SMS) that provide maximum informational value in a low bandwidth environment, and a base of market participants capable of utilizing the new, valuable market information signals.

CHAPTER

5

LAUNCHING SUCCESSFUL E-MARKETS: A BROKER-LEVEL ORDER ROUTING ANALYSIS OF TWO OPTIONS EXCHANGES

5.1 Introduction

Interdependent adoption decisions and network effects can delay the diffusion of new information technologies and prevent organizations from realizing Information Technology (IT)'s value. When technological progress does diffuse into the operational processes of acquiring firms, researchers have sought to identify the economic and sociological drivers of adoption (Abrahamson and Rosenkopf, 1997; Brynjolfsson and Kemerer, 1996; Griliches, 1957; Weber, 2006). Information Systems (IS) research has traditionally focused on pricing, transactions costs, and auction mechanisms (Bakos, 1997; Ghose and Yao, 2011; Overby and Jap, 2009; Tang et al., 2010). A survey of e-markets papers appearing in top journals from 1997 to 2008 found that 90, or nearly half of the 196 papers covered, were on auctions alone (Standing et al., 2010). There is an apparent gap in the literature dealing with issues of successfully opening e-markets.

This paper begins filling this gap by examining the factors influencing options exchange usage among U.S. brokerage firms that led to differing growth patterns for two new e-markets. The results highlight the key role of exchange affiliations in achieving broad market usage. Our findings have implications for operators of new e-markets and participants in the financial trading industry. Moreover, our competing markets setting, and the issue of IT diffusion across firms, are broadly important in the IS field. Many new IT platforms derive their value from the level of usage and the network benefits they generate (e.g. social media websites, packaged software, online auctions). The initial start-up phase is therefore crucial. Technological advantages will not lead to economic benefits unless the adoption decisions and usage patterns of target participants collectively facilitate a successful launch. In this paper we contribute to our knowledge of the factors that can lead to the successful diffusion of a technology, in this case, fully electronic options markets.

Financial markets provide a particularly interesting setting for IT diffusions. The stakes are large. Volumes on U.S. options exchanges in 2010 averaged 15.6 million contracts and $3.4 billion in value per day. Exchange markets depend on the participation of multiple, heterogeneous firms and users, and the liquidity and value of a market grow with its user base. The first all-electronic exchange for trading equity options, the International Securities Exchange (ISE) opened for trading in 2000, and the Boston Options Exchange (BOX), opened for trading in 2004. Compared to the incumbent floor markets, ISE and BOX offer immediate screen based trading, direct user access, and reduced costs. The new exchanges gained trading volumes in competition with four incumbent markets in the U.S. including the largest and oldest, the Chicago Board Options Exchange (CBOE), founded in 1973. While ISE reached 30 percent market share after three years, BOX only achieved 6 percent in the three years from its launch, for reasons that we will examine.

We first develop hypotheses regarding broker order routing to competing electronic exchanges in the presence of affiliation benefits and network effects. Before explicitly testing these propositions, we examine differences in brokers' adoption and attrition across the two exchanges. Then using a panel of six years of quarterly disclosures from 24 major brokerage firms, we model the broker's order routing patterns at the firm level. Estimating fractional regression models of the new markets' growth, we find that 'sociological' factors (affiliations) outweigh the importance of economic factors (network effects) in brokers' order routing decisions to the new markets.

Our results are important for three reasons. First, we advance the academic literature by empirically studying competition between rival electronic exchanges. Prior work generally examined electronic markets versus physical markets. The comparison of alternative IT-enabled institutions is a relatively understudied area of the IS literature (Koh et al., 2010). Second, we find a counterintuitive result in the data that suggests network effects, measured as an exchange's previous quarter market share, are not significant predictors of brokers' order routing levels after controlling for unobserved temporal heterogeneity. Third, the results highlight the importance of creating and maintaining the correct affiliation incentive structure to drive e-market use. Strategies that target a broad base of brokers may not benefit from the network effects as much as previously thought. Management of electronic markets should take this into consideration when designing and updating their affiliation structures.

5.2 Hypotheses

A large body of research has sought to understand the sociological and economic processes underlying the diffusion of new technologies. Empirical data has been used to understand the diffusion process of technological innovations. The seminal work of Griliches (1957) found the diffusion pattern of new, hybrid corn seeds varied by region within the central United States in the period 1932-1956. The adoption of hybrid corn, a new technology, was shown to be a series of interdependent developments involving seed producers and farmers that occurred at different rates in different areas that had different characteristics.

Empirical work looking at IT innovations generally confirms the presence of network effects that influence the expected benefits from a new technology, and thus drive adoption decisions by users. The role of network effects was identified in a study of ATM adoption by banks in the period 1971-1979 (Saloner and Shepard, 1995). At the time, technology was proprietary and ATMs were not yet linked into multi-bank networks. Controlling for a bank's deposit base, it turned out the size of the bank's branch network explained a bank's speed in rolling out ATM machines. More branches led to less rapid ATM adoption. The results suggest predictability in diffusions across firms, and confirmed that anticipated network value leads firms to be earlier adopters of a new technology. A more recent study looks at internet banking adoption and finds that customers are more likely to adopt when local online banking penetration levels are higher (Xue et al., 2011). Another study identified features of spreadsheet software that commanded premium prices, but also identified "positive network externality effects from installed base and from compatibility [that are] as important as any of the intrinsic product features" of the 93 competing software packages in the sample (Brynjolfsson and Kemerer, 1996). A study of the ISE in the period 2001-2004 showed brokers' use was positively related to whether the firm is an online broker, its ISE membership status, and the prior period's overall ISE market share (Weber, 2006).

One challenge for research studying the take up of new IT is that analyses based on sales of an IT product often overstate the true diffusion process (Fichman and Kemerer, 1999). An "assimilation gap" has been identified between the acquisition of software and its deployment. This leads to the conclusion that IT innovations may enjoy robust sales, yet are "not genuinely diffusing in the sense of having a significant impact on the operational processes of acquiring firms". Examining the assimilation of software process innovations in 608 corporate IT departments,

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Fichman and Kemerer develop a model with five variables including department size, education, and internal training activity. The model explained 49 percent of the variance in firms' use of software process innovations (Fichman, 2001). Devaraj and Kohli (2003) studied a sample of DSS usage in eight hospitals. Evidence of benefits were shown to be more strongly linked to the actual usage of technology than to its mere availability. Pac et al. (2010) extended the Bass diffusion model to a competitive environment in which the rival "platforms" have differing network externalities. The optimal adoption times for users are solved for as Nash equilibria, and the paper showed that under competition, the dominance of an incumbent platform translates into lagged response by users to an entrant's innovation.

The above studies document the historic importance of network effects in the diffusion of new technologies. Network effects are also perceived to be important in the context of financial exchanges. Exchanges with greater liquidity tend to have lower spreads and more competitive quotes. Therefore, as the liquidity of the exchange increases, quotes become more competitive and brokers will increase the percentage of orders sent to that exchange. We expect this effect to be apparent in the electronic exchange setting we study here.

HYPOTHESIS 5.1. *As an exchange grows its market share and overall liquidity, the percentage of orders that brokers send to that exchange will increase.*

In contrast to the diffusion economics literature, sociological research emphasizes how know-how or experience with an innovation can be spread across users and become the mechanism that drives network effects (Rogers, 1976, 2003). Abrahamson and Rosenkopf (1997) propose a theory of how the structure of social networks affects the extent of an innovation's diffusion among members. According to the theory, success is a result of knowledgeable advocates, experts and technology vendors promoting early adoption of an innovation. As it becomes more widespread, other forms of institutional pressure — business partners, consultants, etc. — persuade other, similar firms to adopt. They propose that as innovations gain managerial attention, becoming fads and fashionable, their diffusion accelerates, perhaps more so than would be justified on economic benefits alone.

Broker affiliation with an exchange are sociological effects in the context of electronic exchanges. We hypothesize that affiliations can affect order routing in two ways. First, brokers that are affiliated with an exchange will send more orders to that exchange.

HYPOTHESIS 5.2. *Brokers with membership affiliation(s) with exchange A will send a higher percentage of their customer orders to exchange A than brokers without membership affiliation(s) with exchange A.*

Second, affiliating with one exchange can have negative consequences for competing exchanges. With a larger percentage of orders routed to an affiliated exchange, there is less order flow to be routed to competing exchanges.

HYPOTHESIS 5.3. *Brokers with membership affiliation(s) with exchange A will send a lower percentage of their customer orders to exchange B than brokers without membership affiliation(s) with exchange A.*

While sociological research highlights knowledge sharing from adopters to non-adopters, the economics literature principally considers how consumers or firms adopt when they *anticipate* benefits from other consumers or firms using the same technology. The economic benefits may be direct, such as for a fax owner or word processing user gaining when others acquire fax machines or buy software with the same document format. Or there may be indirect benefits, arising from the technology that is widely selected being more likely to survive and have more products compatible with it in the future. For instance, once Blu-Ray went ahead in the format battle for High Definition DVDs, your neighbor can lend you a Blu-Ray disk to play on your machine, generating an indirect benefit an HD-DVD player would not. The first three hypotheses aim to measure whether network or affiliation effects dominate in brokers' decision of where to route orders.

In addition to affiliation and network effects, competitive forces impact brokers' order routing decisions. When BOX enters as a new electronic market, there are four possible outcomes for ISE. The first is that BOX will receive no orders and the status quo will be maintained. A related outcome is that BOX will receive orders that were previously routed to the floor exchanges. This would again have no impact on the percent of orders that are routed to ISE. The third potential outcome is that orders will be routed away from ISE to BOX. This is in line with classic market competition models that predict the introduction of a rival will reduce the market share of closely related competitors. Finally, ISE could experience an increase in order routing. BOX's entry could signal to brokers that electronic trading is not a fad or increase public knowledge of the benefits of electronic trading. In doing so, BOX's entry would "legitimize" the new trading technology. The exact mechanism through which legitimation occurs is outside the scope of this paper. We merely note that, whatever the reason, a second mover may in fact lead to increased market share for the first mover. While we do not know which of these four outcomes will eventually transpire, we expect that BOX's entry will have some impact on the orders sent to ISE.

HYPOTHESIS 5.4. *The opening of a new electronic exchange will impact the percentage of orders sent by brokers to existing electronic exchanges.*

One possible way in which BOX entry can impact order flow to ISE is through changing relative incentives for brokers affiliated to ISE. After BOX opens, brokers are faced with different benefits and costs. The attractiveness of BOX affiliations could cause ISE-afffiliated brokers to change their order routing decisions. We expect that the relative benefits of being affiliated with ISE are reduced when BOX opens and therefore ISE-affiliated brokers will send a lower percentage of their orders to ISE after BOX opens.

HYPOTHESIS 5.5. *The opening of a new electronic exchange will impact the percentage of orders sent to the existing electronic exchange through brokers affiliated with the incumbent exchange.*

5.3 Empirical Context and Data

This section provides an overview of financial market operations with a specific focus on the history of traditional floor-based and electronic options markets. Following this introduction, we describe the multiple data sources used in the empirical analysis.

5.3.1 Financial Market Operations

Financial markets perform a number of basic economic functions. First, they consolidate supply and demand for securities, currencies, and derivatives contracts, and process orders and execute trades. They also disseminate price information. By providing information and price discovery for standardized instruments — stocks, bonds, foreign currencies, and futures contracts — markets play an important role in facilitating capital raising and the transfer of risks. IT makes pricing information widely available and reduces latencies for market communications, which enhances liquidity and provides more choices to investors. As a result, transactions costs have fallen and volumes have risen in most major markets in the past 10 years (Harris et al., 2008).

Second, markets provide infrastructure for transferring ownership and payments, and for enforcing rules and legal contracts. Conflicts of interest and opportunities for fraud arise in markets, so investors require assurance that financial information is reliable (e.g., has been audited), and that trading rules will be enforced. Third, markets intermediate between sources of capital (savers) and users of capital (borrowers), and provide immediacy and liquidity. This means that, for instance, a 'saver' that purchases bonds or call option contracts on a company's stock does not need to hold the bonds or options until their maturity or expiration date. The buyer can reverse the investment decision by selling the bonds or the call options back to buyers in the market. The liquidity of traded financial assets makes them more valuable than other assets that can not be readily converted into cash (Amihud and Mendelson, 1988).

Finally, markets are inter-organizational systems whose success depends on their participant firms, particularly at the time of launch. In such settings, economic forces such as adoption decisions and network effects can determine the impacts of technology as much as technical advantages. The empirical question we answer is how the dynamics of an interrelated, multi-firm environment can support the launch of two electronic options exchanges. Furthermore, we investigate the roles broker affiliation and network effects play in brokers' order routing decisions.

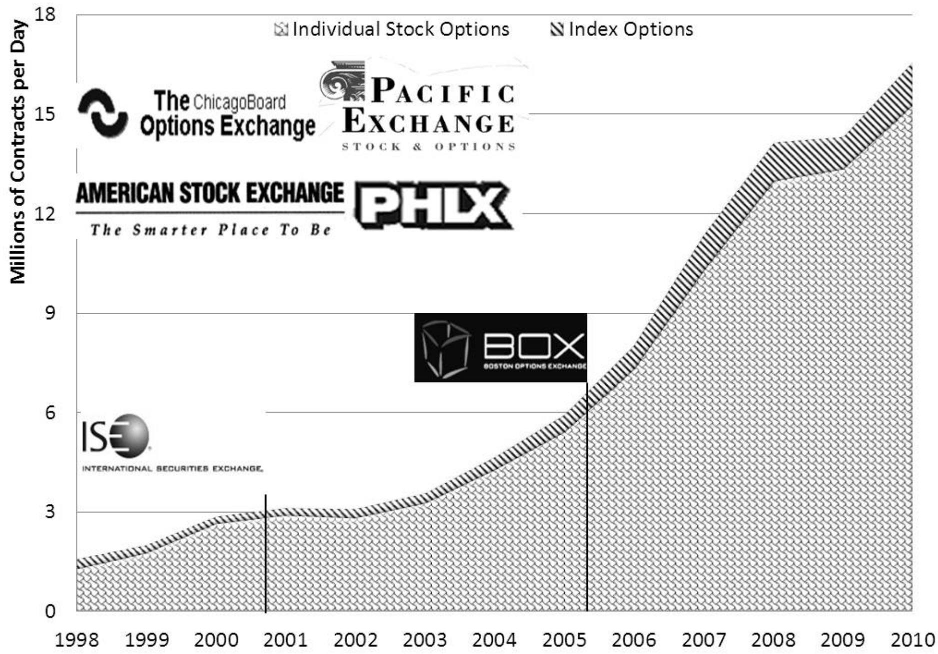

Figure 5.1: Average Daily Equity and Index Options Volume on all U.S. Exchanges, 1998 - 2010. Orders to the markets grew at a compound annual rate of 13.3 percent from 1990 to 2000 and 18.4 percent from 2000 to 2010.

5.3.2 Diffusion of Electronic Options Trading

Options contracts can be either a put or a call. A put (call) option is the right, but not the obligation, to sell (buy) the underlying security at option expiration for a pre-determined price. Each equity contract is for 100 shares of the underlying security. Options contracts began to trade on the Chicago Board Options Exchange in 1973. Three other exchanges for options opened in the next three years. From 1990 to 2000, when the ISE launched, daily average options trading volume grew at a compound annual rate of 13.3 percent. From 2000-2010, volumes rose at a compound annual rate of 18.4 percent, reaching 15.6 million contracts per day by the end of 2010 (Figure 5.1).

The flow of options orders from investors to exchanges is illustrated in Figure 5.2. The order begins with a customer-investor decision (upper-left) to trade a call or put option. The order may be electronically delivered to the broker or take place over the phone. Once the broker has the customer's order, they are obligated to achieve best execution, which means selling at the price of the highest quote, or buying for the customer at the lowest offer to sell. Exchanges will often match the prices/quotes currently offered at competing exchanges. Brokerage firms therefore may need to be

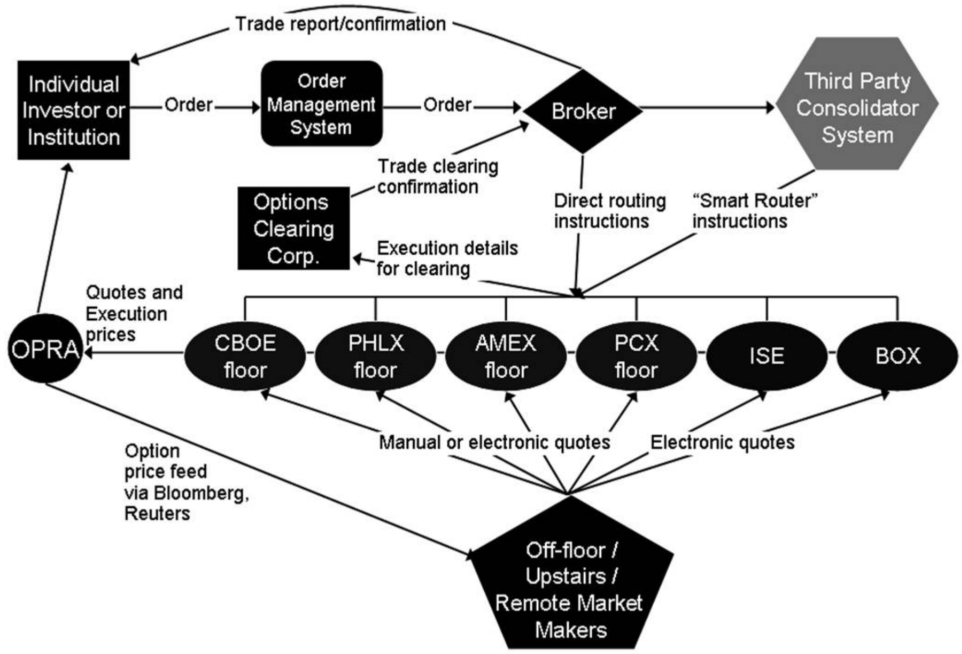

Figure 5.2: Operational flow of orders to U.S. exchanges and market data distribution. Source: Options Pricing and Reporting Authority (OPRA), 2005

incentivized to "route" orders to ISE and BOX, or to use "Smart Routing" systems that are programmed to send orders to ISE and BOX under certain conditions.

Compared with floor exchanges, electronic options markets offer technical advances such as immediate trading, direct user access, and reduced costs. Similar to hybrid corn offering higher yields for farmers willing to invest in new planting and harvesting methods, ISE and later BOX provided brokerage firms the ability to route orders to the new, faster exchanges. The economic diffusion literature suggests electronic exchanges will succeed if they can raise initial expectations that economic value will emerge from growth of their networks and liquidity. Sociological research argues that know-how and enthusiasm for the new markets, communicated among brokers, will lead to greater levels of conversion. IS research has predicted a shift towards electronic markets (Malone et al., 1987). However, even with seemingly large technological advantages, new exchanges often fail to reach sustainable market shares and have to shut down. In the 1980s and 1990s, Intex, Jiway, and Optimark offered new, fully electronic trading platforms but failed to reach critical mass.

ISE and BOX illustrate the critical mass challenges. In their first four years of operation, the two exchanges slowly gained market share from the incumbent floor exchanges. ISE reached a market share of 30 percent after three years. While BOX

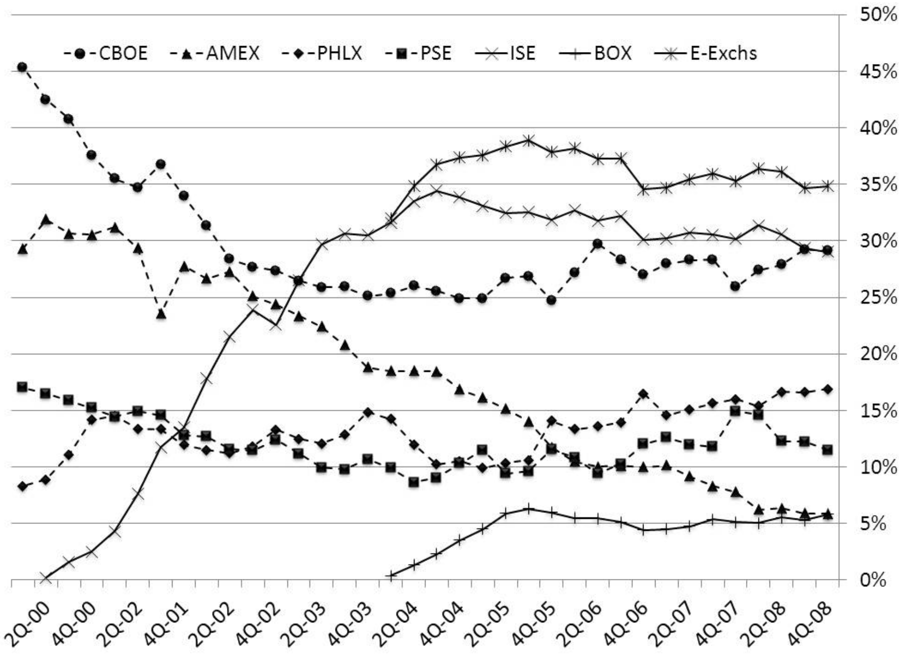

Figure 5.3: Market shares of U.S. Exchanges, 2000-2008. ISE and BOX are electronic competitors to four traditional floor exchanges: Chicago Board Options Exchange (CBOE), American Stock Exchange (AMEX), Philadelphia Stock Exchange (PHLX), and Pacific Stock Exchange (PSE). Traditional floor exchanges are shown with dashed lines while the new electronic exchanges are shown with solid lines. E-Exchs is the total market share for electronic exchanges after BOX entered.

achieved 6 percent market share within two years, it has not increased from that level (Figure 5.3).

Early empirical research into electronic markets generally compared new electronic markets to traditional, manual markets (Clemons and Weber, 1990; Hess and Kemerer, 1994). This paper goes further to compare two electronic markets competing with one another, and with the traditional floor markets they challenged.

5.3.3 Data

We test the hypotheses developed using a panel dataset made up of quarterly observations for 24 major US brokerages from third quarter 2001 through fourth quarter 2006. Since our sample does not contain a complete collection of brokers in the US market, we must ensure it is representative of the industry as a whole. We collected commission revenue data from each broker's annual reports for 2001 to 2006 in addition to aggregate industry commission revenue over the same period.[1]

[1]Data on aggregate total commission revenue was obtained from `http://www.sifma.org/uploadedFiles/Research/Statistics/StatisticsFiles/FI-US-Industry-Financial-Results-SIFMA.xls` on January 27, 2011.

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The revenue from 21[2] of the brokers in our sample made up 70 percent of the entire industry's commission revenue in 2004, the midpoint of our data. Over the 2001 to 2006 period these brokers made up between 69 percent and 78 percent of the industry's annual aggregate commission revenue. Our sample therefore covers the most important U.S. brokers at the time of our analysis.

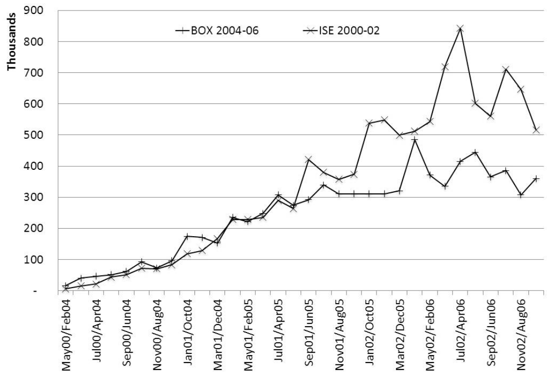
The data on these brokers come from four disjoint sources. First, Securities and Exchange Commission's (SEC) Rule 606 (formerly called Rule 11Ac1-6) requires brokers to publish their routing of equity and option orders on a quarterly basis starting with the third quarter of 2001. The requirement stipulates that every broker must publish the percentage of orders sent to each exchange. This is reported quarterly beginning 3Q 2001 through 4Q 2006 for our sample of 24 of the largest US brokerage firms.[3] The authors collected this data from brokers' websites as the publications were made available.

Second, the total number of contracts traded on each exchange for each quarter was collected from the Options Clearing Corp. We use this data to calculate the market share for each exchange in each quarter. An exchange's market share is a measure of the liquidity in that exchange relative to liquidity in all of the other exchanges. Figures 5.4(a) and 5.4(b) show the growth in the initial months at ISE and BOX were similar in terms of the number of contracts traded per day. In terms of the market share of the exchanges, ISE continued to grow after its first twelve months, while BOX growth stagnated.

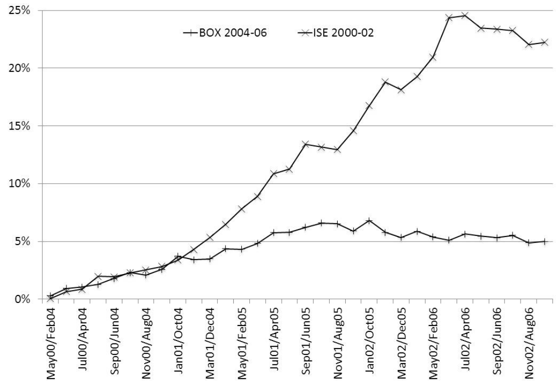
Third is the brokers' membership/affiliation information. The authors hand collected this data from the ISE and BOX websites and through correspondence with managers at the exchanges to determine dates at which firms became members. Table 5.1 summarizes the affiliation categories in each exchange. A detailed description

[2]Three brokers were not included in this calculation because appropriate data was not available. Including these brokers would only increase the total revenue of the brokers in the sample and therefore improve the industry coverage of the brokers in the sample.

[3]Rule 606 mandates that from third quarter 2001 firms must disclose the identity of the market centers that receive 5% or more of customers' orders for: i) NYSE-listed securities, ii) Nasdaq-listed securities, iii) Amex-listed and regional exchange-listed securities, iv) exchange-listed options. The specific disclosures apply are the "Percentage of Customer Orders Having a Market Value Less Than $200,000" for securities, and for listed options, the "Percentage of Customer Orders Having a Market Value Less Than $50,000."



(a) Average contracts per day



(b) Market share of all options contracts traded

Figure 5.4: Electronic exchange order growth. ISE and BOX had similar initial growth in terms of average contracts per day during the first 30 months after launch. However market shares for the two exchanges were only similar in the first eight months.

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ISE
• Launched May 2000 • Market makers must purchase a membership • Membership costs: Primary market makers (PMM): $7.9 million in 2006 Competitive market makers (CMM): $1.5 million in 2008 • One PMM and 16 CMMs in each of 10 option bins • Firms are affiliated with ISE as PMM, CMM or Electronic Access Member (EAM)
BOX
• Launched February 2004 • No seats for brokers to purchase/lease • Unlimited competing market maker participants • Four designated "Price Improvement Process" (PIP) market makers • Firms are affiliated with BOX as Investors, Market Makers, or Participants

Table 5.1: Summary of affiliation structures

of exchange affiliation requirements and benefits is given in the next subsection.

The fourth source is Barron's annual survey of online brokers from 2002 to 2005, which allowed us to separate the brokers into online (OLBs) and full-service categories (FSBs). We use this variable to determine if online brokers, which have adopted a high-technology strategy in the broker space, routed orders differently to the two exchanges. While we have no hypothesis that would suggest differences in order routing, observing a significant difference in order routing for these brokers would provide evidence that an exchange facilitated electronic trading better than the other through better connectivity, timelier support, etc. Table 5.2 reports the mean of the dependent and independent variables in our sample.

Variable	Description	Mean
	Dependent Variables	
ISE	Percent of orders routed to ISE	0.242
BOX	Percent of orders routed to BOX	0.026
	Independent Variables	
OLB	Online Broker Indicator	0.424
ISEPMM	ISE Primary Market Maker Indicator	0.306
ISECMM	ISE Competitive Market Maker Indicator	0.515
ISEEAM	ISE Electronic Access Member Indicator	0.874
BOXINV	BOX Investor Indicator	0.299
BOXPRCT	BOX Participant Indicator	0.743
BOXMM	BOX Market Maker Indicator	0.187
BOXOPEN	BOX Open Indicator	0.536
PREVQTRMSISE	ISE Previous Quarter Market Share	0.280
PREVQTRMSBOX	BOX Previous Quarter Market Share	0.040

Table 5.2: Mean of the dependent and independent variables used in our analysis. Averages for OLB and ISE related variables are calculated over 462 observations. Averages for BOX related variables are calculated over 257 observations due to the later timing of BOX entry.

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5.3.4 Exchange Affiliation Structures

At the midpoint of our data collection in 2004, the ISE listed options on 646 securities. Its market is organized into 10 bins with about 60 stock options in each. A bin has one Primary Market Maker (ISEPMM), and as many as 16 Competitive Market Makers (ISECMMs). An ISEPMM must purchase or lease one of the 10 ISEPMM trading rights. In 2004, eight firms operated as ISEPMMs, with two firms covering two bins each. In 2006, ISEPMM trading privileges for Bin 6 were sold for $7.9 million. The second ISE membership category is Competitive Market Maker. In 2004, 23 firms operated as ISECMMs. An ISECMM must purchase or lease one of 160 ISECMM trading rights, entitling them to enter quotations in the options in a bin. ISECMM trading privileges for Bin 3 were bought for $1.5 million each on December 18, 2003. ISECMM rights were sold for $1.5 million again in 2008. ISEPMMs have greater obligations, but also greater privileges in ISE trading than ISECMMs. The third ISE membership type is an "Electronic Access Member" (ISEEAM). An ISEEAM is a broker/dealer that acts as an order flow provider, and – unlike ISEPMMs and ISECMMs – is not required to purchase membership. There are no limits on the number of ISEEAMs, who pay a monthly access fee to send orders in all of the options traded on the ISE. ISEEAMs cannot enter quotations or otherwise engage in market making activities on the exchange. In 2004, there were 126 ISEEAMs, and in 2009 there were 187.

Exchange	Execution Fee (per contract)	Match / Comparison Fee	Exchange Floor Broker Fee	Total
ISE	$0.15	$0.03	$0.00	$0.18
BOX	$0.20	$0.00	$0.00	$0.20
AMEX	$0.19	$0.04	$0.03	$0.26
Pacific	$0.26	$0.00	$0.00	$0.26
CBOE	$0.24	$0.00	$0.04	$0.28
Philadelphia	$0.20	$0.04	$0.05	$0.29

Table 5.3: Trading fees across exchanges. Fees per contract traded in 2006 are comparable across the six exchanges and cost differentials are not significant in explaining market share gains at ISE or BOX.

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In contrast, BOX doesn't limit the number of brokers within its affiliation designations, nor does it require brokers to purchase seats. BOX Market Makers (BOXMM) are responsible for providing liquidity in the options they have been assigned to, but can freely enter or exit. The market makers on BOX are competing with any number of other market makers. The second BOX membership type is called a participant (BOXPRCT). Similar to the ISEEAM affiliation type, the BOXPRCT is not purchased but a registration requirement for trading on the exchange. The third BOX membership type is an investor (BOXINV). This is different to the other two affiliation types. An investor is a broker that also has an equity stake in BOX.

Data on explicit per trade exchange costs were collected, but the small differences turned out to have no relation to market share changes (Table 5.3). We also learned that volume discounts and rebates made published fees less than reliable measures of actual costs.

5.4 Analysis of Brokers' Adoption and Attrition

Before turning to the econometric analysis of broker order routing, we first examine the pooled data. At the broker level, there are alternative explanations for why BOX did not achieve market share levels comparable to ISE including: (1) fewer brokers used BOX than ISE, (2) brokers used BOX but with not enough volume, and (3) brokers used BOX for a time but then stopped using BOX.

In order to examine adoption and attrition in the highly sensitive post-launch period, we first categorize the brokers into four types:

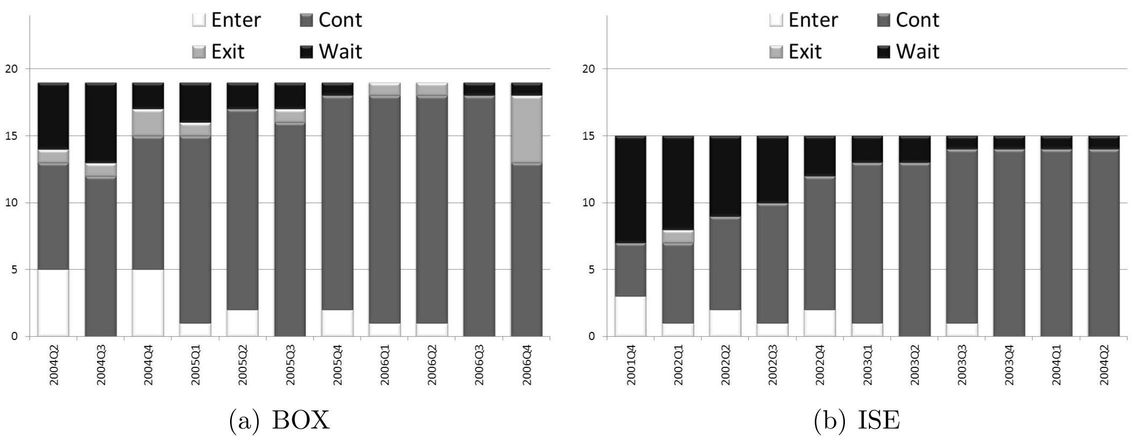

Figure 5.5: Broker categorization. Number of brokers in each category for ISE and BOX in the 12 quarters following exchange opening. ISE had fewer exiting brokers than BOX but BOX had more continuing brokers than ISE.

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1. Continuing brokers are those which submitted orders to the exchange in both the previous and the current quarter.

2. Entering brokers are those which didn't submit orders in the previous quarter but did in the current quarter.

3. Exiting brokers are those which submitted orders to the exchange in the previous quarter but not in the current quarter.

4. Waiting brokers are those which didn't submit orders in either the previous or the current quarter.

If an exchange does not attract enough order flow, it could be the result of brokers not continuing usage (too many brokers exiting the user group), or brokers not entering the user group (too many brokers delaying adoption), or a combination of the two. Starting from when an exchange opened and continuing for 12 quarters, we categorize brokers in this way. This enables us to compare the exchanges on equivalent time spans. In addition, we only consider brokers for which we have order information for all 12 quarters following exchange opening. This prevents overestimation of the impact of each category due to missing data. Figure 5.5 shows the breakdown of brokers in each categorization for both exchanges. Immediately evident is that ISE has fewer exiting brokers than BOX in almost all quarters. However, with the exception of the final quarter, BOX had more continuing brokers

Exchange	Category: Continuing	Entering	Exiting	Waiting
ISE	116 (70.3%)	11 (6.7%)	1 (0.6%)	37 (22.4%)
BOX	156 (74.6%)	17 (8.1%)	13 (6.2%)	23 (11.0%)
POOLED	272 (72.7%)	28 (7.5%)	14 (3.7%)	60 (16.0%)

Table 5.4: Categorization of brokers. Number and percentage of broker-quarters in each category for each exchange. Percentages in a row may not sum to zero due to rounding.

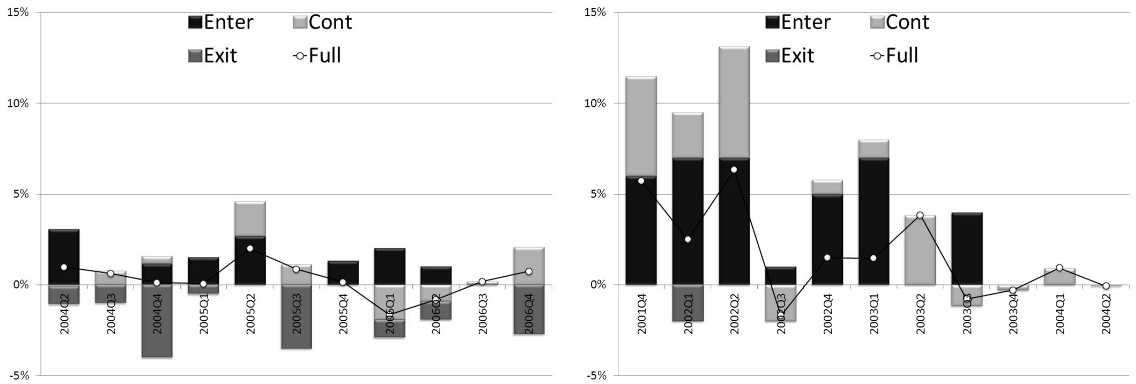
Panel A: ISE			Panel B: BOX		
	Previous Quarter			Previous Quarter	
Current Quarter	Zero	Positive	Current Quarter	Zero	Positive
Positive	22.9%	99.1%	Positive	42.5%	92.3%
Zero	77.1%	0.9%	Zero	57.5%	7.7%

Table 5.5: Brokers' transition in usage. Probability of a broker using ISE (Panel A) and BOX (Panel B) in the current quarter conditional on the previous quarter's usage. Note that columns sum to 100% while rows do not.

than ISE.

Table 5.4 shows the number of broker-quarters in each category for each exchange as well as for the two exchanges pooled together. In addition, it shows the relative percentage of broker-quarters in each category. Using this information, we perform chi-squared tests to determine if the number of broker-quarters in each category for the exchanges is significantly different from the number of broker-quarters in each category for the pooled data. The results of the tests confirm that both ISE and BOX broker categorizations are statistically different than the pooled broker categorizations ($\chi^2 = 100.35$, $p < 0.001$ for ISE and $\chi^2 = 147.01$, $p < 0.001$ for BOX). We conclude that the overall distribution of broker-quarters across the categories is different between the two exchanges.

We also use the data in Table 5.4 to calculate the probability of a broker switching their usage in the current quarter given their usage in the previous quarter. For example, a broker who routed a positive percentage of their orders to an exchange in the previous quarter is either a continuing broker (if their usage is positive in the current quarter) or an exiting broker (if their usage is zero in the current quarter). Similarly, a broker who did not route any orders to an exchange in the previous quarter is either an entering broker (if their usage is positive in the current quarter)



(a) BOX (b) ISE

Figure 5.6: Change in order routing by category. Changes in average shares from quarter to quarter for entering, continuing, and exiting brokers as well as overall change in overage shares for ISE and BOX.

or a waiting broker (if their usage is zero in the current quarter). Table 5.5 shows these probabilities for ISE and BOX. The calculations emphasize the substantial differences between the two exchanges that we see in Figure 5.5. In particular, the chance of an ISE user remaining an ISE user the next quarter is 99.1 percent but it is only 92.3 percent for BOX as 7.7 percent of brokers fail to use BOX the quarter after reporting positive use of BOX.

It is not simply the number of brokers in the categories that determines why ISE reached the market share levels it did while BOX failed to achieve these levels. We must also consider the percent of orders routed to an exchange by the brokers. If brokers start sending orders to an exchange, but only in small amounts, then the exchange may fall short of critical mass. A similar argument applies to brokers that are already sending orders to the exchange. If these brokers stop sending orders to the exchange or decrease the percentage of orders they send to the exchange, then the volume could again be too small. In both cases the positive feedback loop of exchange volume was better engaged for ISE than for BOX.

Figure 5.6 shows the breakdown of changes in averages in each of the broker categories as well as the overall change in average shares. It seems that the average market share sent to ISE by entering brokers is higher than the average market share sent to BOX by entering brokers. In addition, the average change in market share sent to ISE by either continuing or exiting brokers is higher than the average change

	Mean ISE	Mean BOX	t-stat	p-value
Entering Broker	0.0555	0.0196	3.86	0.001
Continuing or Exiting Brokers	0.0105	0.0007	1.45	0.074

Table 5.6: Differences in order routing across broker categorizations. Results of a one-tailed two-sample t-test for differences in the change in average share sent to each exchange for entering and continuing or exiting brokers.

in market share sent to BOX by either continuing or exiting brokers.

Table 5.6 shows the results of two-sample t-tests assuming unequal variances for differences between the change in shares for different categorizations of brokers across exchanges. The results show that brokers using BOX for the first time submitted smaller percentages of their orders compared to those using ISE. Further, brokers continuing or exiting BOX were submitting a smaller percentage of their orders. These two results combine to show that ISE had larger routing percentages and a greater chance of continuing usage, which provided the liquidity advantages needed in order for an exchange to succeed.

BOX had a larger number of users than ISE. However, brokers' lower usage levels and exits from usage resulted in BOX not achieving the market share levels achieved by ISE. These results suggest new electronic exchanges should aim to attract a small number of highly committed users to achieve a successful launch.

5.5 Econometric Specification

In the previous section we showed that brokers' use of ISE was different than BOX. We now turn to a robust econometric analysis to determine how broker characteristics impact their order routing to the two competing electronic exchanges. In the context of electronic exchanges, we explain the percentage of orders sent to a given exchange by a broker in each time period as a function of firm characteristics (broker affiliation with an exchange and whether the broker is an online or full-service broker), and external factors (whether BOX is open and the liquidity of an exchange).

Broker order routing to an exchange is, by definition, bounded between 0 and 1. Two seminal papers demonstrate the econometric issues with estimating a model with a bounded dependent variable Papke and Wooldridge (1996, 2008). These so-called fractional regression models have been gaining momentum in the academic literature as of late. These models take into consideration the bounded nature of the dependent variable and resolve the drawbacks of estimating a linear model such as OLS regression. Additionally, fractional regression models are preferred over alternatives (such as modelling the log-odds ratio in a linear manner) because they allow for observations at the boundary. This is a crucial consideration in our model as there are numerous observations where a broker has not routed any orders to a particular exchange.

The analysis conducted in Weber (2006) failed to take into account these econometric issues. We therefore first verify that these results are robust to a fractional regression model of the form:

$$p_{it} = \alpha_i + \beta_1 ISEPMM_{it} + \beta_2 ISECMM_{it} + \beta_3 ISEEAM_{it} + \tau_t + \epsilon_{it} \tag{5.1}$$

where p_{it} is the percentage of orders sent to ISE by broker i in quarter t, $ISEPMM_{it}$ is a dummy variable taking the value of 1 when a broker is an ISE Primary Market Maker and 0 otherwise, $ISECMM_{it}$ is a dummy variable taking the value of 1 when a broker is an ISE Competitive Market Maker and 0 otherwise, $ISEEAM_{it}$ is a dummy variable taking the value of 1 when a broker is an ISE Electronic Access Member and 0 otherwise, α_i controls for any unobserved broker specific effects, and τ_t are dummy variables for each quarter.[4] The broker fixed effects control for any unobserved, time-invariant differences across brokers. The quarter dummy variables control for quarterly differences that impact all brokers including the previous quarter market share of ISE and any measure of the distribution/concentration of orders across exchanges in a quarter. In addition, they control for any unobserved temporal heterogeneity that may influence a brokers decision to affiliate with an exchange such as changes in competitive strategy enacted by the traditional floor exchanges and customer's demand for near immediate execution. The inclusion of quarter dummy variables prevents identification of the network effect using the previous quarter mar-

[4]When a broker affiliates during a quarter, we scale the 0-1 to reflect the portion of the quarter remaining, e.g. 0.5 if a ISEPMM seat was acquired midway through the quarter.

ket share for ISE, but is robust to arbitrary differences in macroeconomic factors and changes in the competitive landscape through time.

After confirming that previous results related to the impact of affiliation on brokers' order routing decisions are robust to the fractional regression specification with controls for both broker level and temporal heterogeneity, we extend the literature to examine affiliation and network effects under electronic exchange competition. The benefit of observing order routing for both exchanges simultaneously is the ability to identify the impact of network effects, over and above idiosyncratic quarterly shocks controlled for by the quarterly dummy variables, due to differences in the previous quarter market share for the two exchanges. Furthermore, although we cannot determine if online brokers routed more orders to the electronic exchanges than full service brokers because of the broker fixed effects, we can examine whether online brokers routed orders differentially between the two exchanges. Finally, we can examine whether being affiliated with one exchange has a negative impact on the routing to the other exchange and whether the competition or legitimation effect dominates. We estimate a fractional regression model of the form:

$$\begin{aligned} p_{ijt} = \alpha_i &+ \beta_1 BOX_j + \beta_2 OLB_i \times ISE_j + \beta_3 ISEPMM_{it} \times ISE_j \\ &+ \beta_4 ISECMM_{it} \times ISE_j + \beta_5 ISEEAM_{it} \times ISE_j \\ &+ \beta_6 BOXINV_{it} \times ISE_j + \beta_7 BOXMM_{it} \times ISE_j \\ &+ \beta_8 BOXPRCT_{it} \times ISE_j + \beta_9 ISEPMM_{it} \times BOX_j \\ &+ \beta_{10} ISECMM_{it} \times BOX_j + \beta_{11} ISEEAM_{it} \times BOX_j \\ &+ \beta_{12} BOXINV_{it} \times BOX_j + \beta_{13} BOXMM_{it} \times BOX_j \\ &+ \beta_{14} BOXPRCT_{it} \times BOX_j + \beta_{15} MS_{j,t-1} \\ &+ \beta_{16} BOXOPEN_t \times ISE_j + \tau_t + \epsilon_{ijt} \end{aligned} \tag{5.2}$$

where BOX_j is a dummy variable taking the value of 1 when the orders are being routed to BOX and zero otherwise, ISE_j is a dummy variable taking the value of 1 when the orders are being routed to ISE and zero otherwise, OLB_i is a dummy variable taking the value of 1 when the order being routed is from an online broker,

$BOXINV_{it}$ is a dummy variable taking the value of 1 when a broker is a BOX Investor and 0 otherwise, $BOXMM_{it}$ is a dummy variable taking the value of 1 when a broker is a BOX Market Maker, $BOXPRCT_{it}$ is a dummy variable taking the value of 1 when a broker is a BOX Participant and 0 otherwise, $BOXOPEN_t$ is a dummy variable taking the value of 1 when BOX is open and zero otherwise. and $MS_{j,t-1}$ is the aggregate market share of exchange j in the previous quarter. All other variables are as described above. The exchange dummy variables are mutually exclusive meaning that coefficients on the interactions with broker affiliations are differences relative to order routing to that exchange by a broker without that affiliation level.

Finally, we examine how the introduction of BOX impacts broker order routing by brokers that are affiliated to ISE. To Identify the effect, we interact ISE affiliation levels with BOX opening:

$$\begin{aligned} p_{ijt} = \alpha_i &+ \beta_1 BOX_j + \beta_2 OLB_i \times ISE_j + \beta_3 ISEPMM_{it} \times ISE_j \\ &+ \beta_4 ISECMM_{it} \times ISE_j + \beta_5 ISEEAM_{it} \times ISE_j \\ &+ \beta_6 BOXINV_{it} \times ISE_j + \beta_7 BOXMM_{it} \times ISE_j \\ &+ \beta_8 BOXPRCT_{it} \times ISE_j + \beta_9 ISEPMM_{it} \times BOX_j \\ &+ \beta_{10} ISECMM_{it} \times BOX_j + \beta_{11} ISEEAM_{it} \times BOX_j \\ &+ \beta_{12} BOXINV_{it} \times BOX_j + \beta_{13} BOXMM_{it} \times BOX_j \\ &+ \beta_{14} BOXPRCT_{it} \times BOX_j + \beta_{15} MS_{j,t-1} \\ &+ \beta_{16} BOXOPEN_t \times ISE_j + \tau_t + \epsilon_{ijt} \\ &+ \beta_{17} ISEPMM_{it} \times ISE_j \times BOXOPEN_t \\ &+ \beta_{18} ISECMM_{it} \times ISE_j \times BOXOPEN_t \\ &+ \beta_{19} ISEEAM_{it} \times ISE_j \times BOXOPEN_t + \tau_t + \epsilon_{ijt} \end{aligned} \tag{5.3}$$

where all variables are as described above. The three way interactions between ISE affiliations, ISE and $BOXOPEN$ measure changes in order routing by ISE affiliated brokers after the introduction of BOX.

In all three models, we allow for an error structure with arbitrary autocorrelation within a broker and heteroskedasticity across brokers. Clustering errors at the broker level is especially important in models (5.2) and (5.3) where both exchanges are modeled simultaneously. When a larger percentage of orders are sent to ISE there is a lower perentage of orders left to be routed to BOX and vice versa. Failure to account for this would result in incorrect standard errors and conclusions may not be correct.

5.6 Results

We begin this section by confirming the results of Weber (2006) under the more robust fractional regression specification. In addition to the alternative estimation procedure, we include quarter fixed effects instead of lagged exchange market share to control for any temporal heterogeneity that impacts all brokers in a quarter. Column (1) of Table 5.7 shows the results from Model (5.1). Given the inclusion of broker fixed effects in our specification, the best comparison model from Weber's analysis is the firm fixed effects model. In his analysis, Weber found that PMMs and EAMs but not CMMs submitted a significantly larger percentage of their orders to ISE than non-affiliated brokers. In contrast, the current specification finds that only PMMs send a significantly larger percentage of orders to ISE. The change in significance for the EAM affiliation level demonstrates the importance of a correct specification. Instead of high and medium levels of affiliation resulting in significantly higher order routing levels, only the highest levels are important. The inclusion of quarter fixed effects in our specification controls for but does not allow us to separately identify network effects.

5.6.1 Affiliation Effects Under Competition

We now utilize the entry of BOX as a competitor in the e-market space to analyze how affiliations and competition interact as in Model (5.2). The results, in Column (2) of Table 5.7, demonstrate that broker-exchange affiliations are still significant predictors of broker order routing. ISEPMMs send a larger percentage of their orders to ISE but ISECMMs and ISEEAMs do not, suggesting that only brokers with the

VARIABLES	(1) Routing	(2) Routing	(3) Routing
BOX		-0.0629	-0.550
		(1.048)	(1.033)
OLB×ISE		-0.211	-0.238
		(0.692)	(0.670)
ISEPMM×ISE	0.735**	1.013***	1.309***
	(0.349)	(0.308)	(0.345)
ISECMM×ISE	-0.0327	-0.125	-0.0784
	(0.419)	(0.353)	(0.418)
ISEEAM×ISE	-0.887	-0.0336	-0.254
	(0.746)	(0.633)	(0.700)
ISEPMM×BOX		0.547*	0.601*
		(0.316)	(0.311)
ISECMM×BOX		-0.799	-0.983*
		(0.600)	(0.598)
ISEEAM×BOX		-1.983**	-2.137**
		(0.815)	(0.906)
BOXOPEN×ISE		1.273	0.436
		(0.853)	(0.921)
BOXINV×ISE		-0.537**	-0.497**
		(0.240)	(0.224)
BOXMM×ISE		-1.449***	-1.297***
		(0.353)	(0.352)
BOXPRCT×ISE		0.635*	0.760**
		(0.328)	(0.366)
BOXINV×BOX		-0.271	-0.284
		(0.324)	(0.282)
BOXMM×BOX		-0.750	-0.656
		(0.526)	(0.493)
BOXPRCT×BOX		1.597	1.699*
		(0.994)	(0.993)
$MS_{j,t-1}$		4.669	5.125
		(3.475)	(3.152)
ISEPMM×ISE×BOXOPEN			-0.336
			(0.349)
ISECMM×ISE×BOXOPEN			-0.362
			(0.453)
ISEEAM×ISE×BOXOPEN			-0.483*
			(0.257)
Constant	-18.85***	-19.59***	-19.34***
	(1.174)	(1.386)	(1.420)
Observations	462	719	719
Quarter FEs	YES	YES	YES
Broker FEs	YES	YES	YES
Log pseudolikelihood	-155.3	-176.7	-176.2

Table 5.7: Regression results for all models. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

most expensive affiliation levels take their affiliation status into consideration when deciding where to route their orders.

While we find support for the hypothesis that ISE-affiliated brokers send a larger percentage of their orders to ISE, the results for the hypothesis that ISE-affiliated brokers send a smaller percentage of their orders to BOX are mixed. ISEEAMs support the hypothesis that brokers affiliated with an exchange send a smaller percentage of their orders to the other exchange. However, ISEPMMs send a larger percentage of their orders to BOX, although the effect is only significant at the 10% level. The results suggest the ISEPMMs are heavy users of electronic trading in general and do not simply rely on a single platform.

BOX affiliations have similarly mixed results. BOX-affiliated brokers did not send a larger percentage of their orders to BOX than unaffiliated brokers. However, BOXINVs and BOXMMs did send a significantly smaller percentage of their orders to ISE. Similar to the results for order routing of ISEPMMs to BOX, BOXPRCTs send marginally significant larger percentage of their orders to ISE.

The coefficient on BOX indicates the extent to which orders are routed to one or the other exchange after controlling for affiliation effects, network effects, and broker and temporal heterogeneity. The coefficient can be interpreted as the difference between the percentage of orders an unaffiliated broker sends to BOX relative to the percentage of orders an unaffiliated broker sends to ISE. The coefficient is not significant indicating that unaffiliated brokers did not route orders to one exchange over the other. Combining all of the affiliation results together, we conclude that exchanges must carefully decide on a mutually beneficial broker affiliation structure in order to attract a critical mass of participation. Failure to provide the correct incentives will result in low use and could result in complete failure of the exchange.

In contrast to the affiliation levels, previous quarter market share, a measure of network effects, which has traditionally been considered the most important factor for e-market success, is not a significant predictor of broker order routing practices. An important implication of this result is that managers of e-markets cannot rely on network externalities to drive continued use. This conclusion supports the results of the adoption and attrition analysis in Section 5.4 showing a larger number of brokers sending orders to BOX but in lower amounts. The lack of benefits due to network effects suggests that electronic exchanges must solely focus their efforts on identifying and maintaining the correct affiliation structure.

Weber (2006) presented suggestive evidence that OLBs send a larger percentage of their orders to ISE than full service brokers. Targeting OLBs may therefore be a successful strategy. However, OLBs did not send more to ISE or to BOX as evidenced by the insignificant coefficient on OLBtoISE. This is evidence that the broad e-market platform and connectivity was not better at one exchange over the other. Neither exchange can gain a relative advantage by attracting these brokers. However, ignoring OLBs is not an optimal strategy as these brokers may submit a larger portion of their orders to the electronic exchanges in general.

The opening of BOX had little direct impact on ISE after controlling for affiliation as evidenced by an insignificant coefficient on BOXOPENtoISE. BOX order flow could have come at the expense of the floor exchanges. Alternatively, ISE order flow could have increased due to the legitimation effect and decreased due to competitive forces. The two effects would combine to show unchanged order flow as in our regression results. Unfortunately, we cannot determine the specific reason why the coefficient is not significant. Future research can collect necessary data to identify the two effects separately to determine how the two factors interact.

5.6.2 Affiliation Effects Under Increased Competition

The previous results do not identify an aggregate effect of increased competition on ISE order flow. However, it is possible that ISE affiliated brokers changed their order routing as a result of BOX's entry. Column (3) of Table 5.7 contains the results of the regression for Model (5.3). The results for affiliation, network and competition effects are qualitatively unchanged from the previous specification with the exception of a marginally significant coefficient on BOXPRCTtoBOX. We therefore focus exclusively on order routing changes once BOX has opened for brokers affiliated with ISE. When BOX opens, the relative benefits of submitting orders to

ISE must be re-evaluated by these brokers. The results show that ISEEAMs sent a smaller percentage of their orders to ISE after BOX opened for business. Order routing by ISEPMMs and ISECMMs was unchanged following BOX's entry. This further supports the conclusion that retaining heavily affiliated brokers is important to e-market success. When switching costs are low, as in this technology setting, the marginal benefit of low-level affiliations can be easily compromised with the introduction of a closely related competitor.

5.6.3 Managerial Implications

Combined results of the three models highlight the importance of developing and maintaining incentives for brokers to route orders to an exchange. Failure to retain affiliated brokers or loss of a relative affiliation incentive advantage can result in a significant reduction in order routing to an exchange. We conclude that at the time of launch electronic exchanges should spend significant resources to ensure a mutually beneficial affiliation structure. Furthermore, exchanges must react to new competitor entry and changes in competitors' affiliation structures so as to retain an incentive structure that is beneficial for brokers.

Failure to offer the correct affiliation structure can have devastating consequences. A broad use strategy that aims to drive order flow from many different brokers may inevitably fail. E-markets cannot rely on the network effects to maintain order flow from unaffiliated brokers as evidenced by a lack of significance on the previous quarter market share for an exchange. Catering to the unaffiliated masses can be a costly strategy for e-markets as these brokers do not appear to send different amounts of orders to the two exchanges or react to the introduction of new exchanges. Finally, attempting to identify technically capable users, such as online brokers in our setting, will not provide a sustainable competitive advantage over other electronic exchanges.

5.7 Discussion and Conclusions

New electronic exchanges have significant advantages over traditional floor exchanges due to direct user access, faster trading speeds and reduced costs of trading. However, electronic exchanges must differentiate from each other in different ways. This papers examines the roles networks effects and broker affiliations in determining brokers' order routing practices to two new electronic exchanges for options in the US.

We analyze the propensity of a broker to stop using ISE or BOX, and find withdrawals were high at 8 percent per quarter for BOX but less than 1 percent for ISE, which was more "sticky." The commitment of ISE users to continue use of the exchange more than made up for the initially smaller number of ISE users in our sample. This reinforces the conclusion that exchanges require a base of dedicated users to compete successfully, and that a smaller number of heavy users can more than compensate for a low number of users.

Based on our panel of 462 quarterly disclosures from 24 major brokerage firms, we find the growth of new exchanges can be attributed to the characteristics of individual broker-users, and the attraction of a larger market. We also identify significant differences in brokers' order routing practices to two new electronic options exchanges. The models we estimate allow us to test hypotheses that explain individual firms' usage levels and the drivers of new electronic markets' growth. Brokers' order routing to the more successful electronic exchange and the less successful electronic exchange can be attributed exclusively to the exchanges' affiliation structures.

We believe we are the first to compare two competing electronic markets by contrasting order routing models estimated from an empirical data set. We find support for sociological factors influencing diffusion, such as whether it has an e-exchange membership or ownership role. After controlling for broker and temporal heterogeneity, affiliation status is found to be the only significant predictor of broker order routing levels. Unexpectedly, economic measures of the network externality effect, which have traditionally been important factors in the diffusion of new technologies, have no influence on the markets' growth after controlling for temporal heterogeneity. There is no a priori reason to believe that affiliation effects dominate network effects solely in the e-market context we have examined here. Investigation of the relative impact of affiliation versus network effects in competitive market spaces merits further examination.

Finally, unaffiliated brokers did not significantly change their order routing to ISE once BOX opened indicating that competitive effects of a new introduction are seen only through affiliations to the exchanges. From our results, executives of new e-exchanges should allocate their resources strategically at the time of launch. Identifying broker exchange affiliation and incentive schemes is important to building overall liquidity. We can conclude that exchanges should focus on developing a structure that provides brokers with appropriate incentives in order to achieve sustainable order levels. Furthermore, keeping a keen eye on the competitive landscape and reacting to changes in current and prospective competitors' affiliation structures may prove the most beneficial way to ensure continued success. Top management must identify the relative advantages of new entrants' affiliation structures and respond accordingly. A new entrant that provides incentives through a novel affiliation structure can be routed significant orders if the incumbent exchange does not react accordingly. Catering to the masses does not appear to be beneficial as unaffiliated brokers are largely unaffected by the introduction of a new e-market.

In our multi-firm setting with network effects, we believe the empirical methods presented are promising for management researchers who want to explain cross-organizational responses to IT innovation, and generate insights. The results are not limited to analyzing electronic exchanges but, we expect, to many situations where competing IT platforms also benefit from user affiliation and network effects.

CHAPTER

6

HOW IT CAN DISRUPT MARKETS: A SIMULATION ANALYSIS

6

6.1 Introduction

IS research predicted the move to electronic markets seen in recent years (Malone et al., 1987). The move to electronic markets has been thought to decrease search costs and lead to more efficient markets (Bakos, 1991). This transition has made markets more competitive, with multiple parties, usually high frequency traders (HFTs), replacing the traditional specialist position as primary liquidity providers. The competition between HFTs has led to lower bid-ask spreads and larger book depths which have lowered direct and indirect transaction costs (Harris et al., 2008). However, reliance on HFTs as primary liquidity providers has come at a cost. Current financial market regulation and the incentives schemes offered by exchanges to HFTs to trade break down during times of low liquidity. At these specific moments in time, HFTs, unlike the specialists they replaced, are not required to maintain order flow in the market and remove order flows resulting in even less liquidity exactly when liquidity is needed the most. This positive feedback loop exacerbates the instability of market prices leading to "flash crashes" as seen on May 6, 2010 when market indices fell by 998.5 points or nearly 9% from the day's with some stocks falling by more than 90%.[1] A group of exchanges in the US have proposed a new electronic exchange policy aimed at maintaining liquidity in markets when it is most needed in an effort to minimize the degree to which these market aberrations injure market stability.

The proposed "limit up limit down" rules temporarily convert trades that push market prices beyond a threshold to limit orders, allowing the orders to be executed against without causing large intraday price fluctuations. We compare this policy to the status quo where HFTs can leave markets at their discretion and a competing policy where maximum spread requirements are imposed on high frequency traders. Both policies aim to provide price stability during times of severe illiquidity. The rarity of such events makes direct empirical study impossible. For this reason, we simulate an exchange using discrete event simulation. We use the resulting trades to test whether several measures of market quality are better with the proposed limit up limit down market rules or with maximum spread rules. Furthermore, we examine HFT profitability as a secondary analysis. Any market structure change much take HFT profitability into account or risk losing the liquidity provided by HFTs because of decreased profitability resulting in lower market quality in the long run.

Empirical research into market mechanisms has traditionally focused on "normal" trading times, largely ignoring days which are considered aberrations. Amihud et al. (1990) did a study of 12 individual stocks trading on the Milan Stock Exchange from January 2, 1984 - April 30, 1987 and found that opening the market with a call auction results in lower volatility than opening the market in a continuous market. Amihud et al. (1997) studied a group of stocks on the Tel Aviv Stock Exchange

[1] `http://online.wsj.com/article/SB10001424052748704370704575227754131412596.html` accessed on February 14, 2012. Kirilenko et al. (2011) also provide a thorough discussion of the progression of events on May 6, 2010.

that were transferred from call auction trading to a call auction followed by continuous trading. They found that these stocks received a permanent price appreciation of approximately 5.5% after 30 days under the new mechanism providing further evidence that mechanisms matter.

Even without considering periods of large volatility, the shift to electronic markets may not be as beneficial as previously thought. Barclay et al. (2003) find that electronic markets do not always have the best market quality by comparing trades with market makers with those on electronic communication networks (ECNs). Using a month of NASDAQ trades for 150 stocks, they find that ECNs have higher ex-ante transaction costs than trades done with market makers and argue that this is the result of because the market maker preferencing. Similarly, Venkataraman (2001) finds that execution costs are higher on the Paris Bourse than on the NYSE which, at the time of the study, was a traditional floor-based trading structure.

Algorithmic and high frequency trading, like the shift to electronic markets that ultimately enabled it, has been blamed for the flash crash of May 6, 2010. However, the proliferation of algorithmic trading is widely believed to improve market quality (Hendershott et al., 2011; Cvitanic and Kirilenko, 2010; Brogaard, 2012; Groth, 2011; Hasbrouck and Saar, 2010; Hendershott and Riordan, 2011). There is by no means consensus that HFTs are improving market quality. In a study of the May 6, 2010 flash crash, Kirilenko et al. (2011) find that HFTs were not responsible for the crash but contributed to the problem by removing liquidity at key moments throughout the day. Zhang (2010) find a correlation between HFT and market volatility suggesting that HFTs exacerbate volatility leading to lower market quality.

Rather than compare market quality during normal volatility levels, we aim to compare policies during times of extreme volatility. We cannot rely on real-world data to examine the impact that these policies have on market quality and HFT profitability. Flash crashes are, by definition, an abnormal intraday swing in stock prices and therefore have little empirical data with which to perform a rigorous empirical study. We therefore turn to simulated market prices. The results should therefore be interpreted as relative. Simulating a market allows for replication of a sequence of events in addition to market impact.

The simulation used in this paper is based off of one proposed by Schwartz et al. (2006, 2010). They build a discrete event simulation of a market with three types of traders that interact in one of several market structures. In addition, they allow people to interact with the simulation. This creates an environment for interesting behavioural and experimental research into trading and for instruction on trading in a hands-on manner. The current work extends their simulation to include high frequency traders and different policies to keep these traders providing liquidity when it is most needed.

Our results indicate that a clearly dominant trading policy is not available yet. While the proposed limit up limit down policy improves some measures of market quality and increases HFT profitability it also results in lower market quality using other measures and increase HFT overnight risk.

6.2 Market Model

In this section we extend the Schwartz et al. (2006, 2010) simulation model to allow for high frequency traders and modified execution policies. We first describe order types and how orders are matched in the exchanges. We then discuss a general reference price process that can be used to create any number of scenarios. Finally the types of traders in the model are described.

6.2.1 Order Types and the Matching Algorithm

For our market, we consider only two types of orders: market and limit orders. Limit orders specify the volume and price that a trader is willing to transact at. Market orders contain the volume to be transacted but do not contain price information. They execute at the bid and offer prices available in the market at the time the order is submitted.

Upon arrival to the exchange, the orders are submitted to the continuous limit order book (CLOB). In a CLOB, orders are submitted to the order book continuously throughout the entire day. This is the most widely used structure in equity exchanges

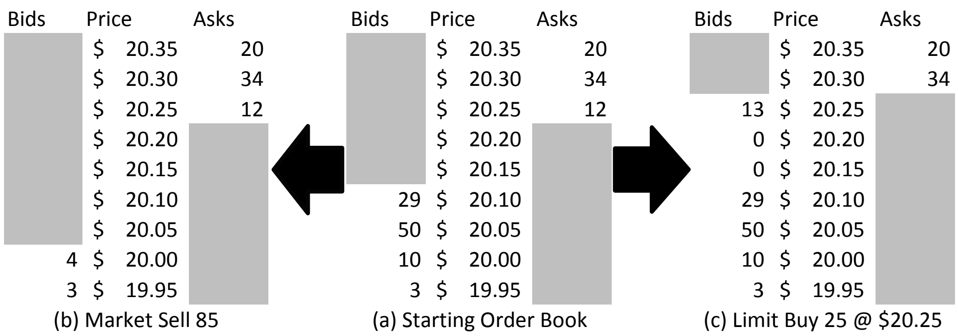


Figure 6.1: (a) the initial order book and the updated order book after (b) a market sell order for 85 and (c) a limit buy order for 25 at $20.25.

around the world. If the order is a market sell (buy) order it is immediately executed if there are orders on the bid (ask) book. On the other hand, if it is a limit sell (buy) order one of two events will occur. First, if the buy (sell) order price is less than the lowest ask (highest bid) price then the order is added to the bid (ask) book. Second, if the buy (sell) order price is greater (less) than or equal to the lowest ask (highest bid) price then the order is matched in trade quantities until there is no further crossing in prices. The remainder of the order is then submitted as a limit order.

Figure 6.1 contains an example of an order book that demonstrates how the matching process occurs. Figure 6.1(a) shows the order book in its initial form. We will look at how the order book changes in two cases: a market sell order for 85 and a limit buy order for 25 at $20.25. In the first case of a market sell order for 85 shares 29 shares would be executed at $20.10, 50 shares would be executed at $20.05 and 8 shares would be executed at $20.00 (leaving 4 shares on the book at this price). The final position of the book is shown in Figure 6.1(b). We now return the book to its initial state, (a), and consider the second case of a limit buy order for 25 shares at $20.25. Here 12 shares would be executed at $20.25. Since there are no more shares at or below the limit order price the remaining 13 shares are entered onto the bid side of the book at $20.25. The final position of the book is shown in Figure 6.1(c). Similar results would happen for market buy and limit sell orders.

In this market, price-time priority is utilized in the order book. This means that the lowest ask (highest bid) is matched first when an executable order arrives. If there is more than one order at the lowest ask (highest bid) then the orders are matched in a first-in-first-out priority. This is a very common prioritization and is used in many markets across the world including the London Stock Exchange.

6.2.2 Reference Price and Information Process Evolution

The reference price process can be any general stochastic process $P_t(\mathbf{X})$ where $\mathbf{X}$ is a vector of (possibly time dependent) state variables. The information arrival process is another general stochastic process $\tau(\mathbf{Z})$ where $\mathbf{Z}$ is a vector of (possibly time dependent) state variables. At the times dictated by the information arrival process, a subset of traders in the market is informed of the reference price $P_{\tau(\mathbf{Z})}(\mathbf{X})$. Specifying $\tau(\mathbf{Z}) = \infty$ means that no traders in the market will observe the reference price. Alternatively, specifying $\tau(\mathbf{Z}) = 0$ means that the informed subset of traders in the market will observe the reference price at all times.

6.2.3 Trader Types

Informed Traders

These traders belong in the subset that observes the reference price at the times specified by the information arrival process. The informed traders are trying to benefit from their private knowledge of the most recent reference price, P*. Because they know this value they will attempt to buy (sell) the stock when the lowest ask (highest bid) is below (above) P*. This strategy will push the trade price towards P* until it is no longer profitable for the informed traders (i.e. P* is within the bid-ask spread). Since these traders are trying to take advantage of a quickly disappearing opportunity they will submit market orders only and therefore are liquidity takers. We refer again to section (a) of Figure 13 for an example. If P* in this case was actually \$20.50 (which is above the lowest ask of \$20.25) then the informed trader would submit a market buy order. Alternatively if P* in this case were actually \$20.00 (which is below the highest bid of \$20.10) then the informed trader would submit a market sell order.

Liquidity Traders

The liquidity traders can be thought of as a combination of people who need money relatively soon or that are trying to disguise their trading intentions. These traders are liquidity providers, unlike the informed traders. This means they tend to place limit orders to the market. However, this is not true for all cases. Some traders may need cash in a short time and some traders may be willing to wait a little while if it means they get a better deal.

Momentum Traders

Momentum traders are trying to take advantage of trends in the market. This trader is attempting to pick up on the information that informed investors are giving to the market. Once they observe an upward (downward) trend in order flow or trade execution they submit a buy (sell) order, in effect betting that the informed traders have observed an updated realization of the reference price without knowing if they have or not.

High Frequency Traders

High frequency traders typically send orders to the market with very short times between the orders. This gives them a faster indication of the direction of order flow. We operationalize this by giving HFTs a noisy signal of P* that is a random number between the latest trade price and the actual P*. HFTs run an inventory model of trading which increases (decreases) their bid and offer prices if they are too short (long). However, they will not submit bids that are above their signal of P* or offers that are below their signal of P*.

6.3 Simulation Setup and Experimental Design

This section formulates the model described in Section 6.2 as a discrete event simulation and describes the experimental design. We first show how the three types of traders, informed, liquidity and momentum, are combined into one order flow. We then discuss the parameters needed for the simulation. We end this section with the experimental design.

6.3.1 Order Flow

We combine the informed, liquidity and momentum traders into one order flow. To do this, we modified the probabilities of buy/sell market/limit orders depending on market conditions. When P* is above (below) the best ask (bid) the probability of a market buy (sell) order is 70 percent. In the remaining 30 percent and when P* is within the bid-ask spread the probability of a limit buy and sell order are both 50 percent. This is augmented to be 70 percent in the direction of a trend if the midpoint of the bid-ask spread has moved in one direction three consecutive times.

6.3.2 Assumptions

While we have attempted to limit the number of parameters in our simulations that are potentially arbitrary, there are still several left to be specified. Where possible we have used parameters that correspond to real markets. For the remaining parameters, we have chosen ranges that reflect real market data and randomized the parameter values across the simulation runs to avoid any bias in our results.

To model the mixture of limit and market orders within the liquidity traders, we have implemented a double triangular distribution for their order submission in a fashion similar to Schwartz et al. (2006, 2010). The distribution is called double triangular because it has two peaks, one at one tick above the best bid and one at the best ask. One benefit of using such a distribution is that since the peaks of the distribution are dependent on the best bid and best ask, this distribution will shift as the order book changes. A symmetric distribution is used for sell orders. Using this distribution results in about 75% of the orders being limit buy orders and the remaining 25% being market buy orders. Our distribution has been set so that the ratio of limit to market orders when informed trader orders are included will be close to these results. Figure 6.2 shows an example of the distribution for buy orders where the best ask price is at \$20.30 and the best bid price is at \$20.10.

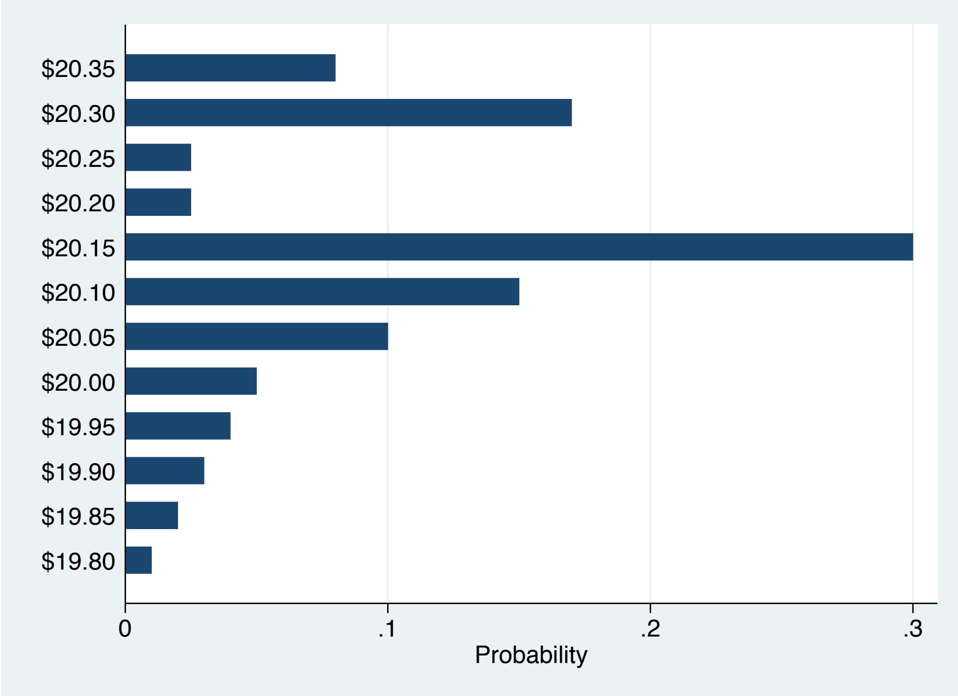


Figure 6.2: Probability distribution used by liquidity traders for a buy order. In this example the best ask is at $20.30 and the best bid is at $20.10. A symmetric distribution is used for sell orders.

The order volume is drawn from a discretized beta distribution. Inherent in this distribution are the two parameters α and β. For our simulation, these two parameters are randomly assigned to be between 1.5 and 2.5 for α and between 4.5 and 5.5 for β. The mean of the beta distribution is $\frac{\alpha}{\alpha+\beta}$ which corresponds to a range of approximately 21 to 36 units using the parameters chosen. In the rest of the paper we use the term "shares" for the units but these can be considered to be 1,000 share lots. These parameters are the same for all traders and will impact both volume and liquidity.

Order arrival times are based on the exponential distribution. To fully characterize this distribution, the only parameter we require is λ_O which is randomly set to be between 2 and 10 seconds according to a uniform distribution.

The market open time, close time, and tick size are set to 9am, 4pm, 1 cent respectively. These were chosen to be close to real-world market trading. This entire analysis could be done in returns space, but without loss of generality the initial P* is chosen to be $20.00.

6.3.3 Experimental Design

To test these hypotheses, we simulate the stock market flash crash under the status quo where there is no restriction on order flow, with several levels of maximum spreads, and with the proposed limit up limit down policy. In framing these scenarios within the current debate surrounding financial markets, rule number 1 can be considered the policy used before the May 6, 2010 flash crash. Rule number 2 requires maximum spreads from high frequency traders and is one potential alternative to the proposed policy. We simulate the policy for maximum spreads of 10 to 20 cents in intervals of 2 cents. Rule number 3 is the new limit up limit down policy suggested by a group of exchanges in the US.

To simulate the flash crash, a large sell order arrives at the market at 11:30AM. The sell imbalance causes prices to quickly fall below the P* value before buying pressure from informed and subsequently momentum traders pushes prices back towards the P* level. We use 10,000 simulations for each policy. All parameters including the P* path are identical for each simulation across the policies but differ from simulation to simulation. This provides us with a controlled way to examine the difference in market quality measures and allows us to attribute these differences to the policy only.

6.4 Measuring Changes in Market Quality

Following Zhang et al. (2011), we classify measures of market quality into three dimensions: activity, liquidity, and information. Activity measures are the number of trades, trading volume and average volume per trade. These measure the broad liquidity in the market (Barclay et al., 2003; Hendershott et al., 2011)

More refined measures of liquidity are classified as liquidity measures. Spread measures such as the quoted spreads, effective spreads, and realized are commonly used in the finance literature (Boehmer et al., 2005; Huang and Stoll, 1996). Depth of volume in the order book is another measure of liquidity (Barclay et al., 2003).

$$\text{Quoted Spread}_t = (\text{Offer}_t - \text{Bid}_t)/(2 * \text{MidPoint}_t) \tag{6.1}$$

where Offer_t is the best offer price, Bid_t is the best bid price, and MidPoint_t is the best offer price plus the best bid price divided by two. The quoted spread is calculated for both orders and trades and measures ex-ante costs of trading.

In contrast to the quoted spread, the effective spread measures actual costs of performing a trade and is therefore only applicable for trades. It measures the price received on the trade as compared to the midpoint between the bid and offer prices when the order was submitted:

$$\text{Effective Spread}_t = \text{D}_t \times (\text{Price}_t - \text{MidPoint}_t)/\text{MidPoint}_t \tag{6.2}$$

where Price_t is the, D_t is an indicator taking the value of $+1$ when the trade is a buy order and -1 when the trade is a sell order and all other terms are as previously defined. We consider τ at 5, 10 and 15 minute intervals for robustness.

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Similarly, the realized spread

$$\text{Realized Spread}_t = \text{D}_t \times (\text{Price}_t - \text{MidPoint}_{t+\tau})/\text{MidPoint}_t \tag{6.3}$$

where τ indicates the time in advance for which the midpoint is measured. The depth on the book at the time of a trade

$$\text{Depth}_t = (\text{OfferVol}_t + \text{AskVol}_t)/2 \tag{6.4}$$

where OfferVol is the total volume on the offer side of the order book, AskVol is the total volume on the bid side of the order book and all other terms are as previously defined.

The only information measure we consider is price impact (Hendershott et al., 2011):

$$\text{Price Impact}_t = \text{D}_t \times (\text{MidPoint}_{t+\tau} - \text{MidPoint}_t)/\text{MidPoint}_t \tag{6.5}$$

where all terms are as previously defined. Similar to the realized spread measure, we consider τ at 5, 10 and 15 minute intervals for robustness.

Finally, we consider HFT profitability and risk as measures of the market quality.

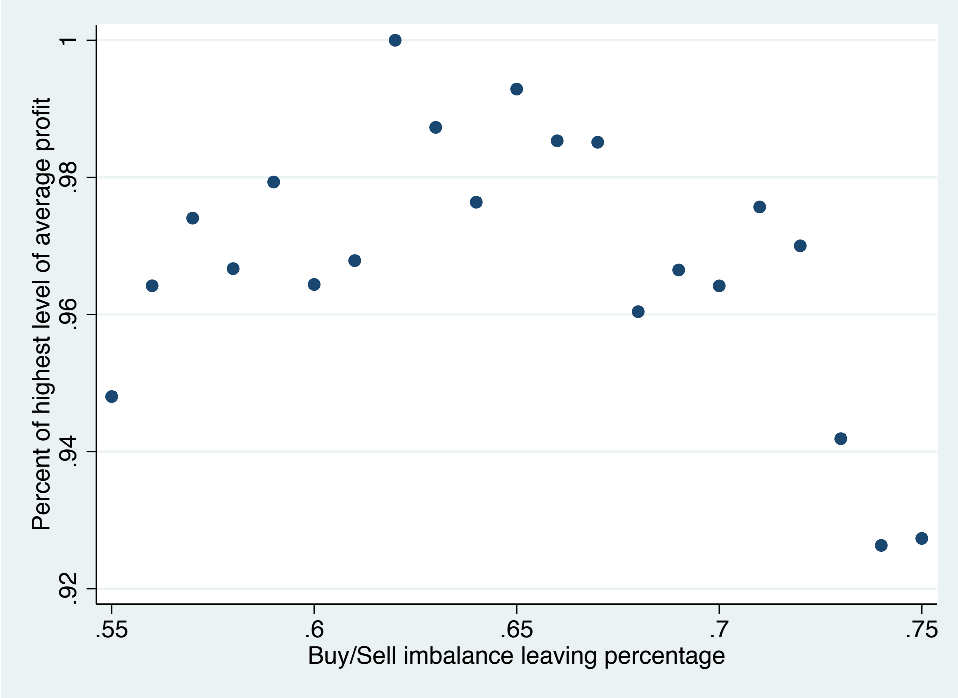

Figure 6.3: Relative profitability over 10,000 simulations for different buy/sell imbalance thresholds for HFTs. Profitability is maximized when HFTs exit at a 62% buy/sell imbalance.

We consider the ending position that an HFT has at the end of the day as a measure of overnight right and average profit including the marked to market price of the shares held at the end of the day and maker taker contributions. Maker taker contributions are cash incentives for traders to provide liquidity to the market in the form of limit orders. The HFT is given 0.25 cents for each limit order share submitted to the market.

6.4.1 Establishing a suitable baseline result

To establish a baseline result to compare the maximum spread and limit up limit down policies, we assume that HFTs will maximize their profits by instituting a policy wherein they exit the market when the buy or sell imbalance crosses a given threshold. To find what this level is, we set the exit level threshold of the HFT to be 55% to 75% in increments of 1% for 10,000 flash crash simulations each. Taking the trade data as output, we find the average HFT profits. Figure 6.3 shows that average HFT profit is maximized if they exit the market when there is a buy/sell imbalance of 62%. We therefore use these simulations as the baseline for comparing market quality measures.

	Exit	Spread 10	Spread 14	Spread 18	Limit Up/Down
Trade Count	1,255.47	1,600.35	1,571.39	1,556.29	1,263.41
	(3.62)	(4.52)	(4.54)	(4.54)	(3.64)
Trading Volume	18,874.06	22,858.37	22,468.65	22,273.79	18,873.05
	(59.02)	(67.56)	(67.87)	(67.70)	(58.97)
Ave. Trade Volume	15.02	14.32	14.34	14.36	14.92
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Table 6.1: Mean and standard error of the mean for different activity measures of market quality for 10,000 flash crash simulations.

6.5 Comparing Policies

This section compares market quality across the different policies in four major dimensions: activity, liquidity, information and HFT profit and risk. Changes in the measures are calculated relative to the baseline established in the previous section. All calculations are from trade and order data from 10,000 simulations. Due to the similarity in the results and for ease and clarity of exhibition, only the 10, 14 and 18 cent maximum spread policies are shown.

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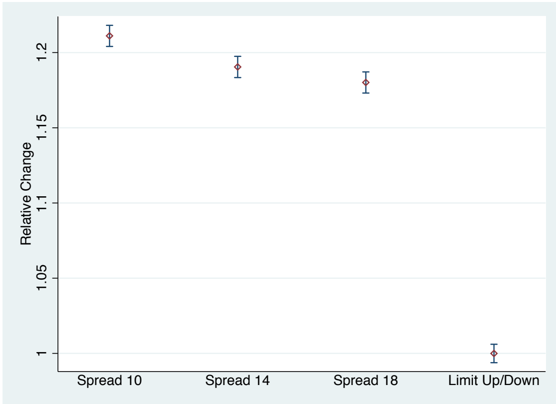
6.5.1 Activity Measures

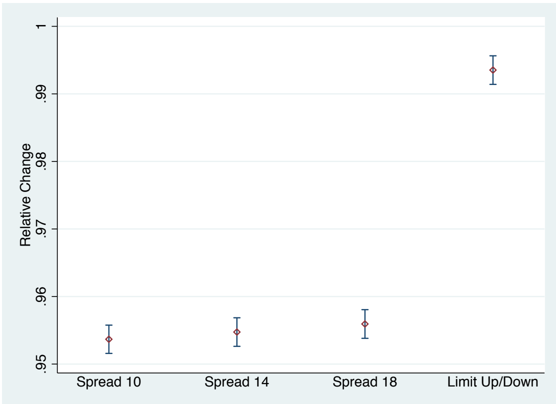
Table 6.1 shows the mean and standard error of the mean for different activity measures of market quality for 10,000 flash crash simulations. In terms of activity, the maximum spread policy appears to result in better market quality as measured by the number of trades and the overall trading volume. However, a reduction in the average volume per trade shows that smaller limit orders were entered by the HFTs to comply with the maximum spread obligations resulting in many small trades. This level of increase could put pressure on the matching algorithms used by exchanges and ultimate result in decreased market quality if the computing engine failed. Careful consideration must be placed on the technological constraints in implementing such a policy.

Figure 6.4 provides a clear graphical picture of Table 6.1. The figures show the relative increase or decrease in the market quality measures relative to the baseline policy where HFTs exited the market with a 62% imbalance threshold. To create the figure, we calculated each measure for a simulation divided by the average of that

(a) Number of trades



(b) Trading volume



(c) Average trade size

Figure 6.4: Mean and 95% confidence interval of activity measures of market quality for maximum spread of 10, 14 and 18 cents and limit up limit down policies divided by the activity measure for the baseline policy over 10,000 simulations.

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	Exit	Spread 10	Spread 14	Spread 18	Limit Up/Down
Quoted Spread	0.25	0.06	0.07	0.08	0.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quoted Spread at Trade	0.29	0.08	0.08	0.09	0.24
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Effective Spread	0.25	0.07	0.08	0.08	0.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Realized Spread - 5 Min.	2.30	20.33	16.16	13.01	2.39
	(0.17)	(0.36)	(0.37)	(0.38)	(0.17)
Realized Spread - 10 Min.	2.30	20.33	16.16	13.01	2.40
	(0.17)	(0.36)	(0.37)	(0.38)	(0.17)
Realized Spread - 15 Min.	2.31	20.33	16.16	13.01	2.40
	(0.17)	(0.36)	(0.37)	(0.38)	(0.17)
Depth	59.68	83.74	81.13	80.44	56.96
	(0.13)	(0.24)	(0.25)	(0.26)	(0.13)

Table 6.2: Mean and standard error of the mean for different liquidity measures of market quality for 10,000 flash crash simulations. All spreads are measured in cents instead of dollars.

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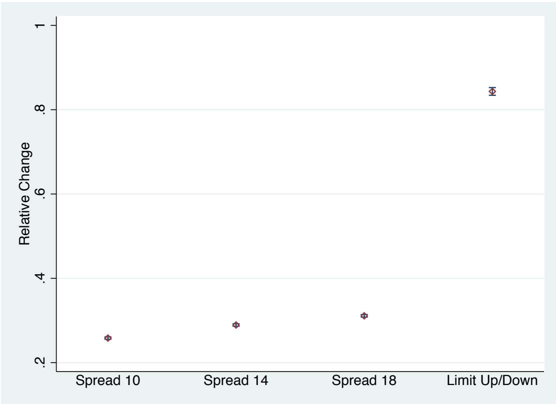
measure for the baseline policy. A value of 1 shows that the metric is unchanged relative to the baseline metric. A value above (below) 1 shows that the metric is higher (lower) than the baseline metric. The figures emphasize the dramatic difference in activity measures of market quality between the maximum spread and limit up limit down policies.

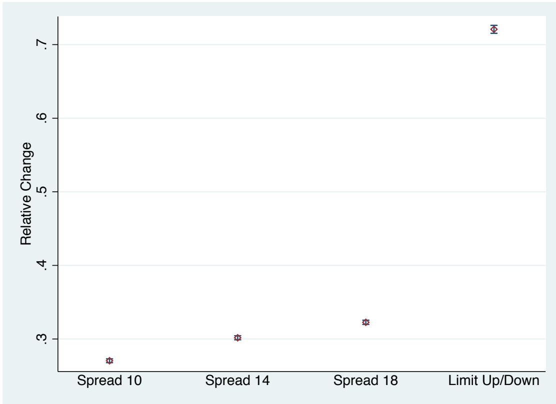
6.5.2 Liquidity Measures

We now examine market quality in terms of liquidity measures. Table 6.2 shows the mean and standard error of the mean for different liquidity measures of market quality for 10,000 flash crash simulations. Spreads are measured in cents rather than dollars for readability. In terms of liquidity, the maximum spread policy is dominant on quoted and effective spreads as well as order book depth. This is to be expected since HFTs effectively set the spread under these policies. On the other hand, the maximum spread policies perform much worse when measured by the realized spread. As the maximum spread increases, the policies appear to be closer in terms of both measures of quality. Regulations will need to weigh the benefits of quoted, effective and realized spreads as well as order book depth in order to make a decision on which of the policies is preferred.

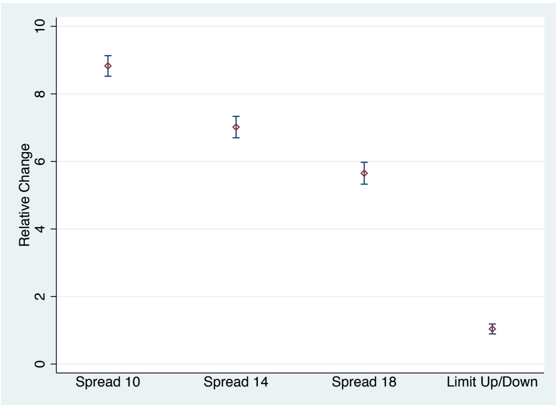
While we have calculated spread measures for 5, 10 and 15 minute intervals,



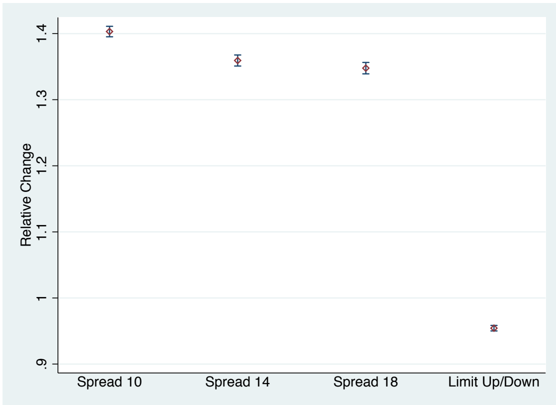
(a) Quoted spread



(b) Effective spread



(c) Realized spread at 5 mins.



(d) Order book depth

Figure 6.5: Mean and 95% confidence interval of liquidity measures of market quality for maximum spread of 10, 14 and 18 cents and limit up limit down policies divided by the liquidity measure for the baseline policy over 10,000 simulations.

	Exit	Spread 10	Spread 14	Spread 18	Limit Up/Down
Price Impact - 5 Min.	-2.05	-20.26	-16.09	-12.93	-2.21
	(0.18)	(0.36)	(0.37)	(0.38)	(0.17)
Price Impact - 10 Min.	-2.05	-20.26	-16.09	-12.93	-2.22
	(0.18)	(0.36)	(0.37)	(0.38)	(0.17)
Price Impact - 15 Min.	-2.05	-20.26	-16.09	-12.93	-2.22
	(0.18)	(0.36)	(0.37)	(0.38)	(0.17)

Table 6.3: Mean and standard error of the mean for different information measures of market quality for 10,000 flash crash simulations. Price impact is measured in cents instead of dollars.

we only plot the realized spread at 5 minutes since the other spreads are nearly identical. We use 5 minutes as opposed to 10 and 15 minutes since it is the time interval the SEC uses to evaluate market quality.[2] The quoted spread at trade is also not plotted due to the similarity between that and the quoted spread at order.

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Figure 6.5 provides a clear graphical picture of Table 6.2 and are calculated in the same manner as the previous figures. The realized spread is a magnitude worse but appears to be getting close to the limit up limit down policy as the spread increases. Unfortunately order book depth does not exhibit the same levels f improvement.

6.5.3 Information Measures

Table 6.3 shows the mean and standard error of the mean for different information measures of market quality for 10,000 flash crash simulations. Price impact is measured in cents instead of dollars for readability. In terms of information, the limit up limit down policy is clearly the best policy. While price impact measures are largely unchanged between the baseline policy and the limit up limit down policy, all of the maximum spread policies exhibit much larger (in magnitude) price impact.

Figure 6.6 provides a clear graphical picture of Table 6.3 and is calculated in the same manner as the previous figures. While increasing the maximum allowable spread appears to improve the price impact, there is still a very clear reduction in market quality associated with the maximum spread policy.

[2]See `http://www.sec.gov/rules/final/34-43590.htm` retrieved on February 23, 2012.

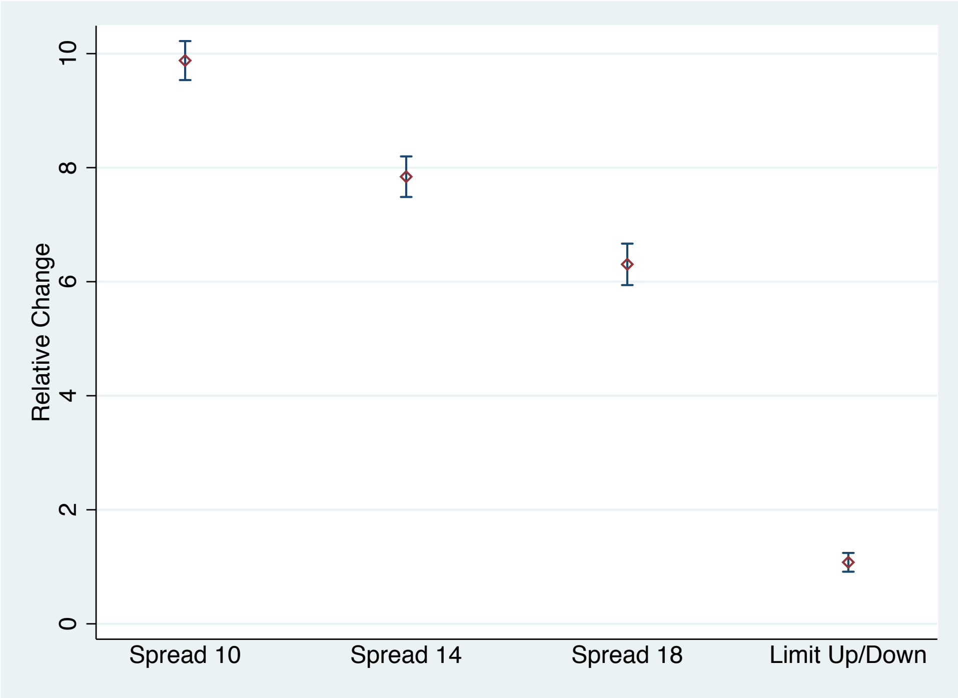


Figure 6.6: Mean and 95% confidence interval of the price impact at 5 minutes for maximum spread of 10, 14 and 18 cents and limit up limit down policies divided by the average price impact at 5 minutes for the baseline policy over 10,000 simulations. Plots are nearly identical for realized spreads at 10 minutes and 15 minutes and are not shown for ease of exhibition.

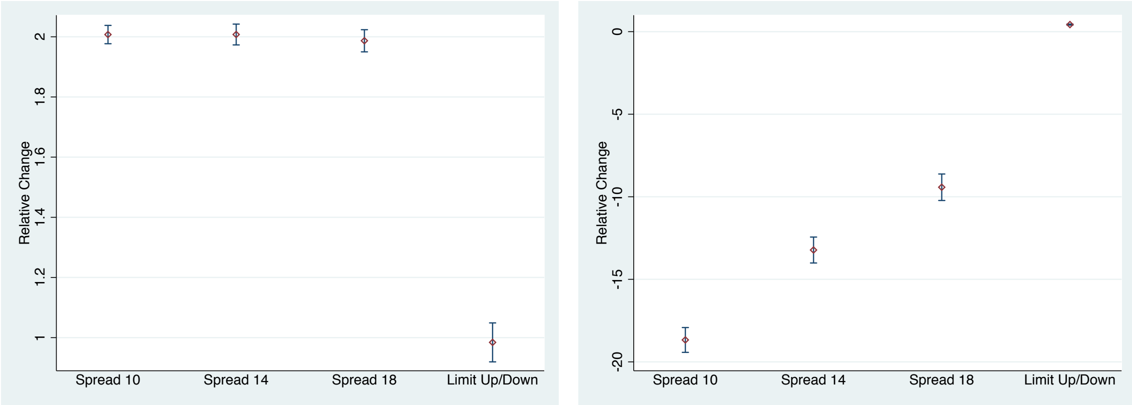
	Exit	Spread 10	Spread 14	Spread 18	Limit Up/Down
HFT Total Profit	79,327.53	159,242.20	159,255.11	157,606.01	78,078.48
	(2,554.42)	(1,231.76)	(1,400.01)	(1,489.10)	(2,619.18)
HFT Ending Position	268.98	-5,022.79	-3,557.52	-2,534.81	115.28
	(3.46)	(103.18)	(107.77)	(110.07)	(4.13)

Table 6.4: Mean and standard error of the mean for HFT profit and overnight risk for 10,000 flash crash simulations.

6.5.4 HFT Profitability and Risk

Finally, we turn to measuring market quality in terms of HFT profitability and overnight risk. Any policy that severely reduces HFT profitability or increases HFT risk relative the status quo could result in HFTs exiting the markets completely. Given the overall benefits of increased liquidity a mass exit of HFTs could leave the markets in worse shape than before. Any policy therefore must attempt to maintain good economic incentives for HFTs to operate in the market.

Table 6.4 shows the mean and standard error of the mean for HFT profitability and ending position or overnight risk for 10,000 flash crash simulations. The nearly doubling of profits for the maximum spread policies relative to the baseline policy suggests that our HFT algorithm may be oversimplified. However, the significant



(a) HFT profit (b) HFT overnight risk

Figure 6.7: Mean and 95% confidence interval of HFT profit and ending position/overnight risk for maximum spread of 10, 14 and 18 cents and limit up limit down policies divided by the HFT profit and ending position/overnight risk for the baseline policy over 10,000 simulations.

6

increase in overnight holdings could be a justification for the larger profit. Overnight holdings represent significant risk for a trader as the trader cannot adjust to new information about the stock which comes to surface overnight. Unfavorable news can lead to drastic losses with little or no ability to minimizes the losses during a closed market.

Figure 6.7 shows these increases in a clear manner. Similar to previous figures, they show the relative increase in the HFT total profit including mark to market value of the stocks they hold and maker taker contributions as well as the overnight position relative to the baseline case. Whether the 10 to 20 fold increase in risk makes up for the nearly doubling of profit would depend on the risk tolerance of the HFT. Without prior knowledge on these measures we cannot make a solid recommendation using this measure. Future research must measure HFT risk aversion levels in order to determine the extent to which an increase in their overnight risk will reduce the number of HFTs in the market and hence lead to lower liquidity in markets overall.

6.6 Conclusion

This paper contributes to the debate about how to minimize the impact of IT-enabled trading practices that can lead to drastic reductions in market quality. These aberrations have long lasting effects on investor confidence and potentially market participation rates. To combat these problems, a new policy has been proposed that converts market orders to limit orders during times of drastic price fluctuations. We analyze the new policy against the status quo to determine if market quality can be improved while maintaining HFT profitability and risk levels. Furthermore, we compare this policy to an alternative policy of setting a maximum spread for HFTs.

Our results show that market quality can be improved with additional regulation while maintaining market quality. There are, however, some caveats. First, not all market quality measures improve and whether market quality improves or degrades is policy dependent. Along those lines, no policy dominates in our analysis suggesting that careful consideration is needed before any long lasting decision is made. Failure to look at HFT risk profiles and the tradeoff of tighter quoted and effective spreads with higher order book depth compared to lower realized spreads and price impact must be debated in great detail. Failure to understand the trade-offs could inadvertently hurt markets.

While we view the current research as a step towards developing better policy for markets under the influence of HFTs, additional research is needed in this area before a clear recommendation can be made on which of the proposed policies will be best for markets to implement. First, alternative/improved HFT algorithms must be tested, possibly working in the same market against each other. The algorithm must take into consideration how HFTs will logically change their algorithm to optimize under the new trading rules. Second, there are several proposed policies that have not been tested in our current analysis. Minimum order lifetimes were not considered because they play no role in our market where order cancellation does not occur in normal trading. However, with more sophisticated HFT algorithms, this policy will undoubtedly need to be evaluated. Similarly, a policy that enforces a maximum order to trade ratio should be evaluated. We leave these extensions of HFT algorithms and policies to future research.

CHAPTER

7

FUTURE RESEARCH OPPORTUNITIES

While this thesis documents and empirically estimates the impact that technology has had on markets and operations, it is by no means the end of the line but merely the ramp to further research. Technology will continue to advance and current advancements will be put to use in unanticipated and unintended ways for novel applications in the years to come. How these developments will impact markets and operations is a rich area for future research. While my research applies in multiple contexts, a thorough coverage of research opportunities in this area is almost surely a paper in itself. I therefore limit the discussion in this chapter to the impact improvements in technology and technology use is having on developing economies. I focus especially on agricultural supply chains and markets but discuss a variety of ways technological advancements are being put to use to improve logistics and information flows. Of particular interest is how improvements in technology and services delivered through existing technological infrastructure can be leveraged in developing economies. I therefore further focus my efforts by examining these topics in the context of developing economies.

7.1 Agricultural Supply Chains/Markets

There are a plethora of opportunities for future research in agricultural supply chains and markets. At the top of my list is a proposed project with Kamalini Ramdas and Nicos Savva that models combinatorial consumer choice, where a consumer must pick K out of N available markets and the objective function is a complex function of the set of market characteristics. We plan to analytically model the market choice decision faced by RML subscribers and empirically test whether the subscribers adhere to this model of choice using the Thomson Reuters data we have already collected. Examining how customers choose those markets can further our understanding of marketing and promotions in developing economies. Targeted advertising in new areas can lead to faster diffusion on the service and reduce the time between introduction of the service and realizing a measurable impact on market quality.

In addition to understanding how farmers choose markets, it will be beneficial to understand what other changes the RML price information service is causing in India's agricultural supply chain. Farmers write letters to the RML management team claiming that the information has allowed them to decide when to sell their produce. Could this be the reason why non-perishable produce does not exhibit higher levels of geographic price dispersion without the information yet still maintains a growing customer base? Do highly perishable crops achieve lower levels of temporal price dispersion given the limited storage options in India?

One lingering question from our research is identifying the role that product and supply chain characteristics play in determining price dispersion decreases from improved informational flows. While our research has shown that perishability plays a role, we do not know the exact reason why. Is this because perishable goods are inherently different or is it the structure/proximity of the markets that enables reductions in price dispersion? Do cash crops or staple crops benefit more from this service? Is this all dependent on the current season? It is important to find the answers to these questions to further our understanding of information flows in markets.

I would like to examine who is receiving the largest benefit from these services. It can be argued that farmers are the least informed party in the system and therefore any increase in information flows will lead to increased income for the farmer at the expense of intermediaries. The current econometric specification cannot answer this question and further refinement and/or data collection will be necessary to determine if farmers are in fact the primary beneficiaries of the service.

Furthermore, farmers claim that RML has: improved their ability to bargain with intermediaries leading to income increases for small farmers; changed the risk profile they face and therefore their choice of which crops to plant; improved crop quality and waste reduction; disintermediation of the supply chain and many other claims. Identifying which of these are actual benefits and which are merely perceived benefits will help in evaluating the net benefit of this type of service and the extent to which society will benefit from subsidizing these services.

Finally, what is the long term benefit of RML? One would expect that daily price information will not be sufficient in the long term as the Indian government attempts to digitize the agricultural markets. Thomson Reuters will need to alter their business model, much as they have done in other contexts, to be continue as a relevant source of information.

7.2 Other Benefits of Technology in Developing Economies

Technology is being put to use to change the way in which business is conducted in developing economies. Retail logistics in developing economies is an extremely fertile area for future research. Uncertainty in demand combines with insufficient infrastructure to make for challenging problems that require innovative solutions.

To face these challenges, new business models using mobile phones to coordinate the exchange of information are put to use every day. For example, Logistimo, Inc. provides mobile phone based supply chain coordination technology utilized by rural retailers in India to track inventory, forecast demand, and provide assistance in optimal order levels to minimize stock-outs.[1] Does this service actually reduce stock-outs or do infrastructure issues need to be solved before improved information can be truly beneficial? Can businesses combine improved information with latent labor supply to fill store shelves in a town where demand unexpectedly spiked by paying individuals to travel to the next town over to pick up a few extra cans of soda?

M-Pesa is service started in Kenya in 2007 that offers simple money transfers via mobile phone.[2] Similar to bank credit, users can deposit and withdraw money, pay bills and transfer money to other users. However, because this service is offered by their mobile phone provider, and not the a banking agent, customers load money at local agents and transfers can easily occur from phone to phone allowing consumers to repay friends for dinner, pay for a taxi, etc. The potential impact of this service is immense but as yet we know only that M-Pesa is convenient. Does traceability of transactions lead to a reduction in fraud? Similar to the credit card, there is now less opportunity for theft. If a mobile phone is stolen and money is transferred then there is evidence of where the money went and capturing the criminal may be easier. Do we therefore see a reduction in crime in areas where M-Pesa is prevalent? M-Pesa also allows for relatively poor individuals to have an account to save their money in. Will this lead to cheaper capital in countries with M-Pesa? Answering these questions will require detailed datasets and either creative identification strategies or randomized experiments to establish causality.

Mobile money such as M-Pesa has also transformed into a way for individuals to be paid for work during their off time. Jana is a crowdsourcing platform of nearly 2.1 billion individuals in over 50 countries are asked to answer simple questions and are paid in mobile phone credits.[3] Could this simple service result in poverty reduction

[1]See `http://http://www.logistimo.com/` for more information.
[2]See `http://www.safaricom.co.ke/index.php?id=250` for more information.
[3]See `http://www.jana.com` for more information.

due to increased incomes? Do businesses in areas where Jana is operating face lower barriers to entry because of the ease of gathering information from consumers about potential new products and services?

On the surface it seems that M-Pesa and Jana are great services with seemingly endless upside potential. However, like high frequency trading, can there be unexpected detrimental outcomes to relying on these services? If so what kind of policies should be instituted to minimize the occurrence of these negative outcomes?

Logistimo, M-Pesa and Jana are only three of the services offered via mobile phone in developing economies. A simple Google search demonstrates the vast options of services available. Where do we put our resources? What are the drawbacks of supporting effort A versus effort B? Which services can be business-led and which should be left to NGOs? Empirically measuring and comparing the impact of these services will be challenging, but doing so can have a large impact on our understanding of information systems and supply chain coordination technologies in developing economies.

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