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THE DIGITAL PROVIDE: INFORMATION (TECHNOLOGY), MARKET PERFORMANCE, AND WELFARE IN THE SOUTH INDIAN FISHERIES SECTOR*

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When information is limited or costly, agents are unable to engage in optimal arbitrage. Excess price dispersion across markets can arise, and goods may not be allocated efficiently. In this setting, information technologies may improve market performance and increase welfare. Between 1997 and 2001, mobile phone service was introduced throughout Kerala, a state in India with a large fishing industry. Using microlevel survey data, we show that the adoption of mobile phones by fishermen and wholesalers was associated with a dramatic reduction in price dispersion, the complete elimination of waste, and near-perfect adherence to the Law of One Price. Both consumer and producer welfare increased.

I. INTRODUCTION

How do improvements in information impact market performance and welfare? Economists have long emphasized that information is critical for the efficient functioning of markets. For example, two of the most well-known results in economics, the First Fundamental Theorem of Welfare Economics (i.e., competitive equilibria are Pareto efficient) and the "Law of One Price" (LOP) (i.e., the price of a good should not differ between any two markets by more than the transport cost between them) rely heavily on the assumption that agents have the necessary price information to engage in optimal trade or arbitrage. These results

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reflect some of the most fundamental functioning of and advantages to a market economy; when goods are more highly valued on the margin in one market than another, a price differential arises and induces profit-seeking suppliers or traders to reallocate goods towards that market, reducing the price differential and increasing total welfare in the process. In reality, however, the information available to agents is often costly or incomplete, as emphasized by Stigler [1961]. In such cases, there is no reason to expect excess price differences to be dissipated or the allocation of goods across markets to be efficient. Yet despite the fact that information is both central to economic theory yet so limited in reality, there are few empirical studies assessing the effects of improvements in information. Thus, questions such as how much market performance can be enhanced by improving access to information, how much society gains from such improvements, and how those gains are shared between producers and consumers remain largely unanswered. In this paper, we examine these questions by exploiting the introduction of mobile phones in the Indian state of Kerala as a natural experiment of improved market information.

Beyond its prominent place in economic theory, the effect of information on market performance and welfare is also relevant to the debate over the potential value of information and communication technologies (ICTs) for economic development. Many critics argue that investments in ICTs should not be a priority for low-income countries, given more basic needs in areas such as nutrition, health, and education.[1] However, this argument overlooks the fact that the functioning of output markets plays a central role in determining the incomes of the significant fraction of households engaged in agriculture, forestry, or fisheries production in low-income countries; for most of the world's poorest, living standards are determined largely by how much they get for their output. Additionally, the functioning of these markets determines the prices and availability of food, fuel, and other important consumer goods. However, in most developing countries, markets are dispersed, and communications infrastructure is poor. Producers and traders often have only limited information, perhaps knowing only the price in a handful of nearby villages or the nearest town, so the potential for inefficiency in the allocation of goods across markets is great. By improving access to

1. Perhaps ironically, Microsoft's Bill Gates has been among the most prominent of such critics [Gates 2000].

information, ICTs may help poorly functioning markets work better and thereby increase incomes and/or lower consumer prices. In fact, it has become increasingly common to find farmers, fishermen, and other producers throughout the developing world using mobile phones, text messaging, pagers, and the internet for marketing output.[2] However, while there is some macrolevel evidence that ICTs promote economic growth [Roller and Waverman 2001], the microlevel evidence has been purely anecdotal. Thus, the case of mobile phones in Kerala will also allow us to examine whether ICTs can play a role in promoting welfare in developing countries; while much has been written about how the uneven spread of ICTs has created a "digital divide" between rich and poor countries, considerably less is known about the benefits such technologies can provide the latter.

Fishing is an important industry in Kerala. For consumers, fish is a dietary staple [Kurien 2000]; over 70 percent of adults eat fish at least once a day, making it the largest source of many important nutrients, such as protein. Further, over one million people are directly employed in the fisheries sector [Government of Kerala 2005]. However, a significant limitation to fish marketing is that while at sea, fishermen are unable to observe prices at any of the numerous markets spread out along the coast. Further, fishermen can typically visit only one market per day because of high transportation costs and the limited duration of the market.[3] As a result, fishermen sell their catch almost exclusively in their local market. In addition, there is almost no storage (due to costs), and little arbitrage on land due to poor road quality and high transportation costs; ultimately, the quantity supplied to a particular market is determined almost entirely by the amount of fish caught near that market. Table I provides suggestive evidence of the resulting inefficiency. The table presents data for fifteen beach markets in northern Kerala, listed in north–south geographical alignment, on average fifteen kilometers apart. The first column provides the prevailing "beach price" (price paid to fishermen by wholesalers or retailers) for a kilogram of sardines on Tuesday, January 14, 1997, at 7:45 A.M., just before

2. To cite just a few examples from popular media sources, such behavior has been observed in Thailand and the Philippines [Arnold 2001]; Kenya [England 2004]; Congo and South Africa [LaFraniere 2005]; Bangladesh and China [Alam 2005]; and even the case of fishermen in Kerala examined here [Rai 2001].

3. During the period of study, most beach markets were open only from 5:00 to 8:00 A.M.

TABLE I
PRICES AND EXCESS SUPPLY AND DEMAND IN FIFTEEN SARDINE BEACH MARKETS

	Price (Rs/kg)	Excess buyers	Excess sellers
Kasaragod District			
Hosabethe	6.2	0	0
Aarikkadi	4.0	0	0
Kasaba	0.0	0	4
Kanhangad	7.2	0	0
Thaikadappuram	9.7	11	0
Kannur District			
Puthiangadi	8.7	2	0
Neerkkadavu	6.9	0	0
Ayikkara	8.4	1	0
Thalassery	4.3	0	0
New Mahe	6.2	0	0
Kozhikode District			
Chombala	9.9	15	0
Badagara	0.0	0	11
Quilandi	9.8	12	0
Puthiyangadi	0.0	0	6
Chaliyam	6.4	0	0

Data from the Kerala Fisherman Survey conducted by the author. The first column contains the average 7:45–8:00 A.M. price of sardines in each market on Tuesday, January 14, 1997, in rupees per kilogram. The markets are listed in north–south geographic alignment; starting from Hosabethe, the distance in kilometers between each market and the next is: 12, 14, 15, 15, 24, 15, 6, 14, 9, 8, 7, 15, 10, and 16. "Excess buyers" represents the number of buyers who leave the market without having purchased enough fish, and "excess sellers" is the number of fishermen who leave the market without selling their fish.

the effective market closing. There is a great deal of price variation, with some markets having an effective price of zero (fishermen arrive to find all buyers have departed) while others range from 4.0 to as much as 9.9 rupees per kilogram (Rs/kg; \$1 US $\approx$ 36 Rs). Note in particular that Badagara has a price of zero while Chombala and Quilandi, both within fifteen kilometers, have prices of 9.9 and 9.8 Rs/kg, respectively. Since an average boat on this day was carrying 381 kg of fish and the fuel cost of traveling fifteen kilometers was about 205 Rs, a boat arriving at Badagara was forgoing as much as 3,400 Rs in profit. Columns (2) and (3) show this from another perspective, with data on the number of "excess buyers" (wholesalers/retailers who report having bought no fish because of high price or inadequate supply) and "excess sellers" (fishermen who arrive at a market and find no buyers and therefore dump their catch in the sea). The inefficiency is clear; while at Badagara there are eleven fishermen dumping their catch unsold, there are twenty-seven buyers within fifteen kilometers who are about to leave without purchasing any fish. Provided there are no other barriers to arbitrage, if fishermen had price information for all locations, the market should achieve an outcome where price dispersion is reduced, fish are allocated across markets more efficiently, waste is reduced or eliminated, and total welfare is increased (though how those gains will be shared between consumers and producers is ambiguous).

Beginning in 1997, mobile phone service was gradually introduced throughout Kerala. Since most of the largest cities are coastal, many base towers were placed close enough to the shore that service was available twenty to twenty-five kilometers out to sea, the distance within which most fishing is done. By 2001, over 60 percent of fishing boats and most wholesale and retail traders were using mobile phones to coordinate sales. Thus, the case of Kerala provides an ideal setting for exploring the effects of information on market performance and welfare. Using microlevel survey data spanning this period, we find that price dispersion was dramatically reduced with the introduction of mobile phones; the mean coefficient of variation of price across markets (the standard deviation divided by the mean) declined from 60–70 to 15 percent or less. In addition, there were also almost no violations of the Law of One Price once mobile phones were in place, compared to 50–60 percent of market pairs before. Further, waste, averaging 5–8 percent of daily catch before mobile phones, was completely eliminated. Overall, the fisheries sector was transformed from a collection of essentially autarkic fishing markets to a state of nearly perfect spatial arbitrage. In addition, fishermen's profits increased on average by 8 percent while the consumer price declined by 4 percent and consumer surplus in sardine consumption increased by 6 percent (though relative to average household expenditure, the latter effect is extremely small).

The remainder of this paper proceeds as follows: Section II discusses a simple model that generates predictions for the effects of mobile phones on market performance. Section III discusses the data and empirical strategy. Section IV examines the effects of mobile phones on price dispersion, waste, and adherence to the LOP. Section V provides estimates of the welfare effects, and Section VI concludes.

II. Information, Price Dispersion, and Welfare

II.A. The Model

Assume there are two towns along a coastline, each with an equal measure continuum of fishermen who leave in the morning and fish in the "catchment zone" near their town. Each fisherman's catch is a random variable with an identical distribution across individuals, but there is positive correlation for fishermen within a catchment zone. Specifically, we assume that a fisherman's catch depends on the density of fish, d, present in their catchment zone on a particular day, where each zone can be in either a high (H) or low (L) density state. The catch for fisherman i thus follows the distribution $f(x_i|d)$, where x_i takes on values from zero to $x_{\max}$. $f(x_i|d)$ satisfies the Monotone Likelihood Ratio Property, so that $f(x_i|H)/f(x_i|L)$ is increasing in x, i.e., high catches are more likely in the high than low density state. For ease of exposition, we further assume that each zone has an equal probability of H and L each day, equal to one-half, and that these realizations are independent across zones.

At the end of the day, there is a competitive fish market in each town, with many small buyers and sellers.[4] We assume the aggregate demand curve $P(Q)$ is identical for the two towns, where Q is the quantity supplied to the market, with $P'(Q) < 0$. The default option for each fisherman is to sell their catch in their local market. However, they could pay a transportation cost τ and sell in the other market (but they can only visit one market per day).[5] On observing their own catch, each fisherman updates their assessment of the state of their catchment zone; a higher catch suggests the zone is more likely to be in a high density (low price) state and raises the possibility they could benefit from

4. In most studies of consumer search (see Stiglitz [1989] for a review), there are many sellers but only one at any particular location; consumers incur a cost for each price quote they wish to receive (i.e., each seller they visit). Each seller then knows that a consumer arriving at their store will only search for an additional quote if the expected price difference exceeds search costs, in effect creating market power for sellers. In the present case, search (by fishermen) is among competitive markets, each with many buyers and sellers, emphasizing the pure arbitrage value of information. In this way, our analysis differs from much of the theoretical and empirical literature on search.

5. In practice, it is rarely possible to visit more than one market per day because markets are open for only a few hours (and travel for boats loaded with fish is time consuming and expensive). Because overnight storage by fishermen, traders, or consumers is prohibitively expensive, fish must be consumed the day they are caught. Markets close early because fish sold later would not have enough time to travel the supply chain from beach to consumer.

selling in the other market.[6] The fishermen's problem is to maximize profits by choosing where to sell their fish.[7]

THEOREM 1. When each fisherman observes only their own catch, there exists a Bayes–Nash equilibrium where

1. there is a threshold $x(\tau)$, with $x'(\tau) \geq 0$, such that all fishermen with catch greater than this value sell in the nonlocal market and all those below sell in the local market,
2. price dispersion between the markets exceeds (per unit) transportation costs when the markets are in opposite states (the prices are equal when they are in the same state), and
3. there is a threshold, τ^*, above which all fishermen always sell in their local market.

The proof is in the Appendix. Theorem 1 is intuitive. When fishermen observe only their own catch, those with the highest catches switch to the nonlocal market both because they assess a higher likelihood of being in an H state and because their high catch yields a greater expected gain in profits for a given expected price difference. Fishermen with lower catches either believe it is more likely they are in a low-density (high price) state, or recognize that even if they are in a high-density state, fishermen with greater catches will switch markets and reduce the equilibrium expected price difference to where it is no longer profitable for them to switch, given their small catch. For the marginal fisherman who switches markets, the expected equilibrium price difference equals the (per unit) transportation cost, τ/x. Since fishermen do not know the state of either zone with certainty, arbitrage is less than the full-information optimum, and the equilibrium price differential exceeds transportation costs. As transportation costs increase (or it becomes more difficult to predict a zone's state from one's own catch) there will be less switching and greater price dispersion in equilibrium. In the extreme, there may be no switching because even for the fisherman with the highest catch, the expected gain is less than the transportation costs.

6. We assume $x'[P(Q_L) - P(Q_H)] > \tau$, $0 < x' < x_{\max}$, i.e., in the default state there are profitable arbitrage opportunities.

7. We assume fishermen are risk neutral, since in practice this is a high frequency (daily) repeated game and smoothing income or consumption over such short intervals is relatively easy.

We now introduce a search technology, where for a cost, Ψ, fishermen can learn the catch in both zones. The fisherman's problem now is whether to purchase the technology and where to sell their catch.

THEOREM 2. There exists a Bayes–Nash equilibrium where

1. there is a threshold $x(\psi)$ such that all fishermen with catch greater than this value purchase search (and switch markets when the zones are in opposite states) and
2. a reduction in Ψ weakly reduces price dispersion between the markets.

In the Appendix, this theorem is proven for the case where $\tau \geq \tau^*$, since in practice there was no arbitrage before mobile phones were available (as shown later).[8] As before, fishermen with the greatest catches are more likely to believe they are in a high density zone and thus may gain by switching. They are therefore more likely to purchase search.[9] And although it entails an additional cost for potential arbitrageurs, introducing the search technology makes it possible for arbitrage to occur despite the fact that it would not otherwise because when search costs are sufficiently small, the threshold catch for purchasing search is lower than the threshold for engaging in "blind" switching. Search allows fishermen to learn the state of both zones with certainty and thereby avoid unprofitable switching (transportation costs incurred when both zones turn out to be in the same state, and transportation costs plus lower revenue when the blind arbitrageur guesses incorrectly and switches from an L to an H market). Search is purchased up to the point where the expected gain from arbitrage (net of transportation costs) equals the cost of search. And thus as the cost of search declines more fisherman

8. When $\tau < \tau^*$, i.e., there would be some switching even without the search technology, Theorem 2 continues to hold but only when search costs are below a threshold, $\Psi^*(\tau)$. If search costs are high relative to transportation costs, two cases can arise: (1) no fishermen purchase search, but those with the highest catches switch anyway (as in Theorem 1 or 2) fishermen with the highest catches switch without purchasing search and fishermen with catches in an intermediate range below this buy search and switch only when the zones are in opposite states.

9. In a repeated game where the search technology is a durable good like a mobile phone, fishermen purchase search when the discounted stream of expected gains from switching markets over the life of the technology exceeds the cost. Variation in the stream of expected gains can arise through heterogeneity in average catch (such as due to boat size or fishing gear) or arbitrage costs [due to the type of engine or boat (construction material or hull shape, for example) being used]. The basic conclusions of the model continue to hold.

purchase it and engage in arbitrage when the markets are in opposite states, thereby reducing price dispersion.

The model is easily extended to include waste (as observed in Table I). Waste arises because of saturation points in demand; while consumers purchase more fish on days when the price is low, there is a limit to how much they will purchase on any given day, especially since fish cannot be stored.[10] Thus, if the maximum quantity demanded at each town is less than the total catch when a zone is in the H state, there will be waste in a market whenever the corresponding catchment zone is in state H and there is no arbitrage. Lower search costs reduce waste by facilitating arbitrage when the zones are in opposite states.

It should be noted that while we have modeled it here as a problem of costly information, excess price dispersion or a lack of arbitrage may arise for other reasons, such as constraints on trade. For example, fishermen may collude to punish buyers who purchase from nonlocal fishermen, buyers may collude to punish fishermen who sell outside their local market, or there may be interlinked transactions, such as when a fisherman receives credit from a buyer and in exchange must always sell to them (as seen in Giné and Klonner [2002] and Platteua [1984]). In these cases, reduced search costs would not lead to more arbitrage unless it affected the ability to sustain such constraints. However, in the region of study, fishermen reported no such constraints on fish marketing during this period.

II.B. Welfare Effects

Beyond reducing price dispersion, increased arbitrage due to search will also result in a net welfare gain. Figure I shows the basic analytics of the welfare change under the assumption of perfectly inelastic supply (which we show approximates the Kerala case). The figure shows consumer and producer surplus when one zone is in an H state and the other is in an L state, with and without arbitrage. In the L zone, consumers gain $A+B$ while producers lose A and gain C when X fish caught in the H zone are added to the market. These changes can be viewed as a net gain of $B+C$ and a transfer of A from producers to consumers (because

10. Fish retailers in Kerala report that saturation points affect their decision-making; there is a limit to how much fish they are willing to buy because they know that only a certain number of customers are likely to come to their market on a given day, and there is a limit as to how much any customer will buy, even at arbitrarily low prices.

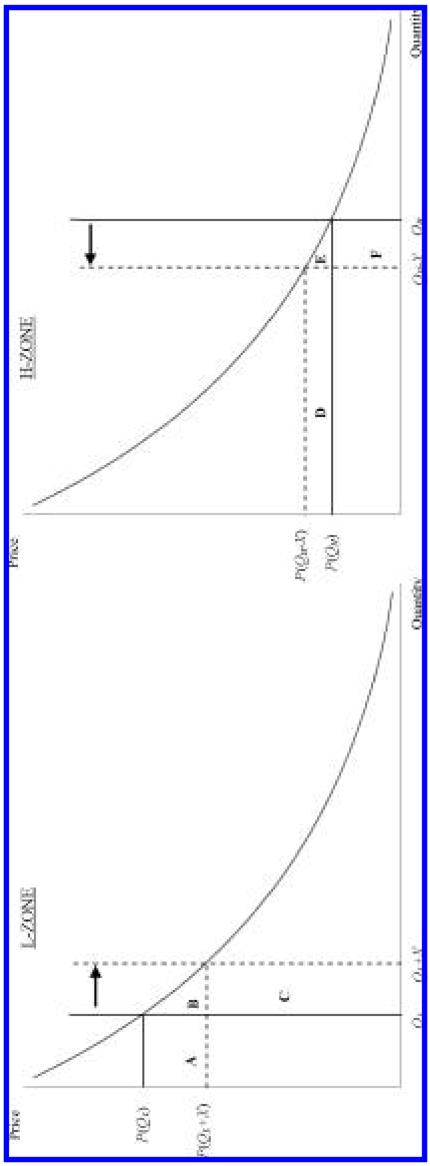

FIGURE I
Changes in Welfare Associated with Arbitrage

the Q_L fish caught in that zone are now sold at a lower price than if there were no arbitrage). In the H zone, consumers lose $D+E$, while producers gain D and lose F, representing a net loss of $E+F$ and a transfer of D from consumers to producers (since the $Q_H–X$ nonarbitraged fish now sell for a higher price). The net change in total welfare is the difference in the two quasi-trapezoids, $(B+C)-(E+F)$ or $\int_{Q_L}^{Q_L+x}$ P(Q)dQ $-$ $\int_{Q_H-x}^{Q_H}$ P(Q)dQ. Provided the demand curve has a negative slope everywhere between Q_L and Q_H, the net change is always positive because the two quasi-trapezoids have the same base, while $P(Q_L+X)$ is always greater than $P(Q_H–X)$, by at least the transportation cost of the marginal switcher. The difference reflects the increase in welfare from moving X fish from where on the margin they were valued less (the high catch, low price market) to where they were valued more (the low catch, high price market). These gains can be substantial, especially when the no-arbitrage price difference is large.[11] Further, the net gain will exceed total search and transportation costs.[12] Finally, while we used consumer surplus to measure welfare, Hicksian compensated demand curves can be substituted for the Marshallian curves in Figure I; since the former are always downward sloping, the same prediction of a net gain in welfare holds for other measures of welfare.

The size and direction of the net transfer from consumers to producers, $D-A$, as well as the net gain for each group, $(C-A)+(D-F)$ for producers and $(A+B)-(D+E)$ for consumers, will depend on the shape of the demand curve (in particular, the price elasticities of demand at the initial quantities) and the amount of arbitrage. Thus, how the net welfare gain is shared between the two groups, and whether, in fact, one group gains while the other loses

11. For example, with a linear demand curve, $P = a - bQ$, the percent increase in welfare from arbitrage is given by $Xb(Q_H - Q_L - X)/(a(Q_H + Q_L) - .5b(Q_L^2 + Q_H^2))$. If $a = 10$, $b = .1$, $Q_L = 1$, and $Q_H = 9$, the gain ranges from 12 percent when one fish is arbitraged to 27 percent when four fish are arbitraged (though we must subtract transportation costs).

12. Consider the case with zero search costs and perfect information; in equilibrium, the price difference between the markets is $\tau/\tilde{x}$, where $\tilde{x}$ is the catch of the marginal fisherman who switches. Then the area of rectangle C above $P(Q_H–X)$ (i.e., the top point of the quasi-trapezoid $E+F$) is $(X/\tilde{x})\tau$. Note that $(X/\tilde{x})$ is greater than the total number of fishermen who switch markets since all fishermen who switch will have catch at least as great as the marginal switcher. Thus, this area alone (and thus $C-(E+F)$ alone) is greater than total transportation costs incurred (τ times the number of fishermen who switch). A similar argument holds when search costs are added.

in response to increased arbitrage, is *a priori* ambiguous.[13] In general, the gains for consumers will be smaller (or even negative) when demand is less price elastic. However, it is possible for both groups to gain, especially if arbitrage also reduces waste.

In analyzing the welfare effects of commodity price stabilization via storage, Newbery and Stiglitz [1981] and Wright [2001] emphasize the direct benefits of reduced price risk, including possible supply responses. However, later we will argue that these issues are not relevant for the present case. Perhaps the most significant aspect of welfare omitted so far is the consequence for consumers of reduced price variability. Consumers may prefer prices that vary day to day because they can engage in intertemporal substitution, waiting to consume only on days when prices are low.[14] However, consumers also gain from less variable prices because they can have smoother consumption and because they do not need to incur costs to visit markets to find out if prices are low since the price is stable and predictable. The net effect for consumers of more stable prices is therefore ambiguous.

III. Data and Empirical Strategy

The data for this paper come from surveys in Kerala's three northern districts, Kasaragod, Kannur, and Kozhikode. We conducted a weekly survey of 300 sardine fishing units[15] throughout the region of study on Tuesdays of every week from September 3, 1996, to May 29, 2001. We first chose fifteen of approximately thirty-five beach markets (which also serve as the ports or "landings" for the fishing units) throughout the districts, selected so that there was one market, on average, every fifteen kilometers. Within each landing, we made a census of all sardine fishing units and then randomly chose ten large (twenty-eight feet or above) and ten small units. Interviewed in the afternoon regarding that morning's

13. Synthesizing earlier work by Waugh [1944] and Oi [1961], Massell [1969] argued that consumers lose and producers gain when price is stabilized at its arithmetic mean if supply shocks drive price variability, and vice versa for demand shocks. However, this result relies on the assumption of linear supply and demand curves.

14. Though if all consumers engaged in such substitution, there would be no price variation even without arbitrage. If everyone tried to consume on low price days, the increased demand would drive up the price, and vice versa on high price days. Demand shocks would perfectly offset supply shocks; in equilibrium the price today must equal the expected price tomorrow; though heterogeneity or limited substitution could generate equilibrium price variation.

15. A unit may contain more than one boat, as with ring seine units that use several boats and nets to encircle fish.

market, each fishing unit was asked for the amount of fish caught, market of sale, quantity sold, sale price, time of sale, costs, and whether they used a mobile phone. Fishermen were also asked for wind and sea conditions (calm, mild, severe) and approximate fishing location (indicated on a map).

Mobile phone service first became available in Kerala on January 1, 1997. However, due to high investment costs and uncertainty about demand, service was introduced gradually throughout the state, rather than all at once. For the three districts we consider, service became available first in Kozhikode (Kozhikode city, effective January 29, 1997), followed by Kannur (Kannur city on July 6, 1998, and Thalassery on July 31, 1998) and then Kasaragod (Kasaragod city and Kanhangad on May 21, 2000). Figure II shows the timing of mobile phone service availability, where the area of study is divided into three regions based on service provision; each region also contains five markets from our survey. While mobile phone service was not explicitly planned to accommodate fishermen, the cities listed above are coastal, so with a service radius of about twenty-five kilometers for each mobile phone tower, service became available for much of the range in which sardine fishing occurs (ten to thirty kilometers from the shore).

Mobile phones spread widely among fishermen and buyers. Figure III provides data on adoption by fishermen in each of the three regions. The vertical lines represent the dates at which service became available in each region (weeks twenty-three, ninety-eight, and 198 in our sample). In each case, adoption increased rapidly before reaching a plateau after a few months.[16] The ultimate penetration level is high, ranging from 60–75 percent across the regions.[17] The phones were widely used for fish marketing; while almost all sales before mobile phones were conducted via beach auctions, fishermen with phones, often carrying lists with the numbers of dozens or even hundreds of potential buyers, would typically call several buyers in different markets before deciding where to sell their catch, in essence conducting a virtual auction, and committing to a price while at

16. The flat part of the graph in region I was caused by long-term contracts among the first adopters. (Such contracts were not required during other periods.)

17. By contrast, adoption among the general population was less than 5 percent during this period.

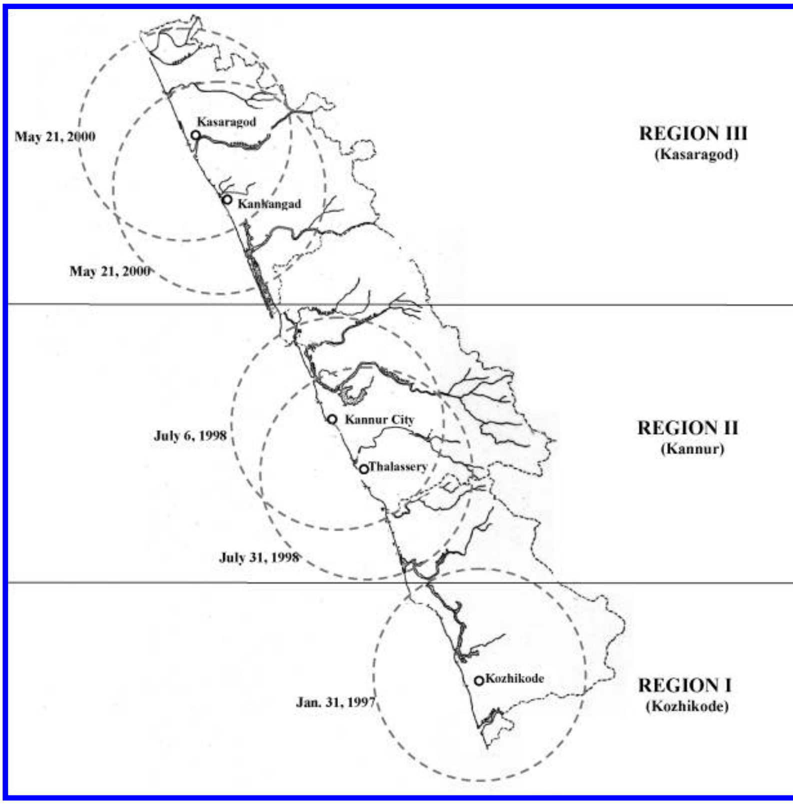

FIGURE II
Spread of Mobile Phone Coverage in Kasaragod, Kannur, and Kozhikode Districts

sea.[18] In general, phones were bought by the largest boats first, since they faced the largest potential gains to arbitrage and were also more likely to be able to afford the phones, which were initially expensive (as much as $100 US).

Our empirical analysis compares how changes in the outcomes of interest (price dispersion, waste, and welfare) correspond to the staggered introduction of mobile phones across the regions. We can break the sample into four time periods: period 0

18. Both fishermen and buyers report that it is extremely rare for a negotiated deal at sea to be broken later, largely due to the need to establish a credible reputation.

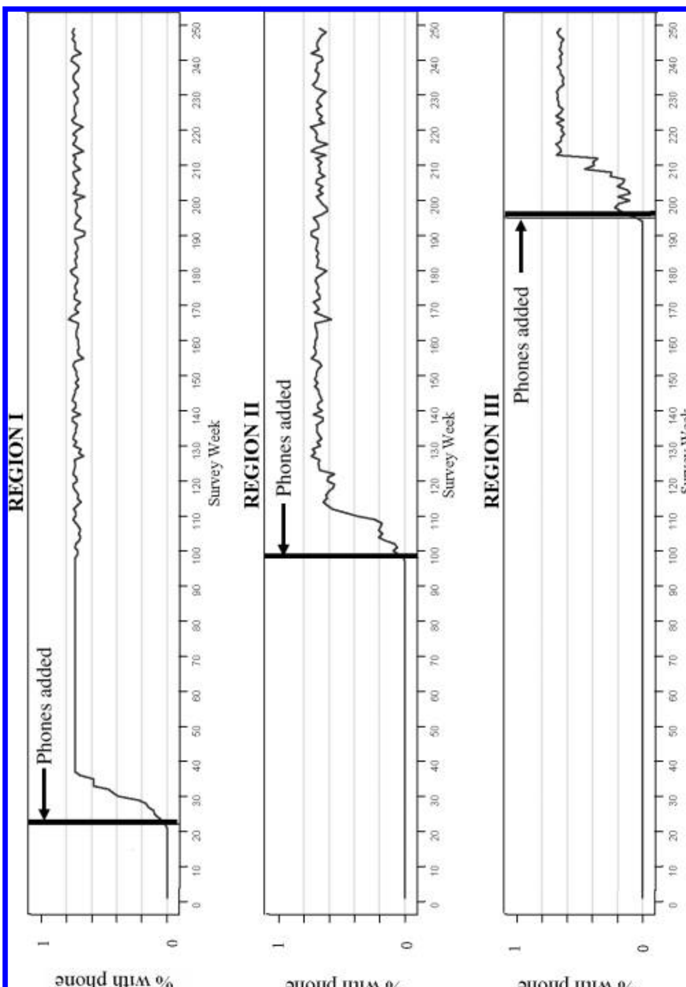

FIGURE III
Mobile Phone Adoption by Fishermen
Data from the Kerala Fisherman Survey conducted by the author.

(weeks one to twenty-two), when no region had mobile phones; period 1 (weeks twenty-three to ninety-seven), when only region I had mobile phones; period 2 (weeks ninety-eight to 197), when regions I and II had mobile phones; and period 3 (weeks 198–249), when all three regions had mobile phones. Letting $\bar{Y}_{r,p}$ represent the average value of the outcome of interest in region r in period p, we can examine the change in $\bar{Y}$ in region I between periods 0 and 1, i.e., before versus after the introduction of mobile phones in the region, relative to the change over the same periods for regions II and III, i.e.,

$$(\bar{Y}_{I,1} - \bar{Y}_{I,0}) - (\bar{Y}_{II,1} - \bar{Y}_{II,0}) \tag{1}$$

and

$$(\bar{Y}_{I,1} - \bar{Y}_{I,0}) - (\bar{Y}_{III,1} - \bar{Y}_{III,0}). \tag{2}$$

Similarly, for the addition of mobile phone service to region II, we can compare

$$(\bar{Y}_{II,2} - \bar{Y}_{II,1}) - (\bar{Y}_{I,2} - \bar{Y}_{I,1}) \tag{3}$$

and

$$(\bar{Y}_{II,2} - \bar{Y}_{II,1}) - (\bar{Y}_{III,2} - \bar{Y}_{III,1}). \tag{4}$$

Finally, for region III, we can compare,

$$(\bar{Y}_{III,3} - \bar{Y}_{III,2}) - (\bar{Y}_{I,3} - \bar{Y}_{I,2}) \tag{5}$$

and

$$(\bar{Y}_{III,3} - \bar{Y}_{III,2}) - (\bar{Y}_{II,3} - \bar{Y}_{II,2}). \tag{6}$$

To control for other factors that may influence market outcomes, we estimate,

$$Y_{r,t} = \alpha + \sum_{r=\mathrm{I}}^{\mathrm{II}} \beta_r \mathrm{Region}_r + \sum_{p=1}^{3} \beta_p \mathrm{Period}_p + \sum_{r=\mathrm{I}}^{\mathrm{II}} \sum_{p=1}^{3} \beta_{r\_p} \mathrm{Region}_r * \mathrm{Period}_p + \gamma Z_{r,t} + \varepsilon_{r,t},$$

where Z is a set of control variables that may affect the extent of arbitrage, including wind and sea conditions and the price of fuel. This strategy eliminates fixed differences across the regions and

TABLE II
MOBILE PHONE INTRODUCTION AND CHANGES IN FISH MARKETING BEHAVIOR

	Period 0 (pre-phone)	Period 1 (region I adds phones)	Period 2 (region II adds phones)	Period 3 (region III adds phones)
Percent of fishermen who fish in local catchment zone				
Region I	0.98	0.99	0.98	0.98
	(0.003)	(0.001)	(0.001)	(0.002)
Region II	0.99	0.98	0.99	0.99
	(0.002)	(0.001)	(0.01)	(0.001)
Region III	0.98	0.98	0.98	0.99
	(0.002)	(0.001)	(0.001)	(0.001)
Percent of fishermen who sell in local catchment zone				
Region I	1.00	0.66	0.63	0.62
	(0.00)	(0.005)	(0.005)	(0.006)
Region II	1.00	1.00	0.64	0.58
	(0.00)	(0.00)	(0.004)	(0.006)
Region III	1.00	1.00	1.00	0.70
	(0.00)	(0.00)	(0.00)	(0.005)
Number of fishing units				
Region I	83	85	85	89
Region II	69	74	75	75
Region III	53	55	54	56

Data from the Kerala Fisherman Survey conducted by the author, using fishermen's self-report of fishing location and market of sale. The catchment zone for each town is the area of sea defined by lines extending out to sea at the midpoint between a town and its nearest neighbors to the north and south. Regions and periods are as defined in the text. Standard errors in parentheses.

common trends or changes over time in factors that affect all three regions equally, such as changes in state fisheries policy or boat, engine, or storage technologies. The identifying assumption is that in the absence of the introduction of mobile phone service, there would have been no differential changes in the outcomes across these regions. We discuss potential challenges to this assumption in detail in Section IV.

Tables II and III demonstrate the identification strategy. Table II shows that prior to the introduction of service (period 0), in all three regions fishermen both fished and sold their catch almost exclusively within their local catchment zone.[19] However, once mobile phones are introduced in region I, while all fishermen

19. Catchment zones are defined as the area of sea closest to each fishing village (i.e., a line extending out to sea at the midpoint between a village and the nearest town to the north or south).

TABLE III
PRICE DISPERSION AND WASTE IN KERALA SARDINE MARKETS

	Period 0 (pre-phone)	Period 1 (region I adds phones)	Period 2 (region II adds phones)	Period 3 (region III adds phones)
Max–min spread (Rs/kg)				
Region I	7.60	1.86	1.32	1.22
	(0.50)	(0.22)	(0.10)	(0.44)
Region II	8.19	7.30	1.79	1.57
	(0.44)	(0.29)	(0.19)	(0.16)
Region III	8.24	7.27	7.60	2.56
	(0.47)	(0.27)	(0.25)	(0.34)
Coefficient of variation (percent)				
Region I	.68	.14	.08	.07
	(0.07)	(0.01)	(0.01)	(0.01)
Region II	.62	.55	.12	.08
	(0.04)	(0.04)	(0.01)	(0.01)
Region III	.69	.57	.54	.14
	(0.09)	(0.04)	(0.03)	(0.02)
Waste (percent)				
Region I	0.08	0.00	0.00	0.00
	(0.01)	(0.00)	(0.00)	(0.00)
Region II	0.05	0.04	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Region III	0.07	0.06	0.06	0.00
	(0.01)	(0.01)	(0.01)	(0.00)

Data from the Kerala Fisherman Survey conducted by the author. Period and regions are as defined in the text. The max–min spread is the difference between the highest and lowest 7:30–8:00 A.M. average price on a given day among the five markets making up each region, in year 2001 Rs/kg. The coefficient of variation is the standard deviation of the 7:30–8:00 A.M. average price on a given day across the five markets within each region divided by the mean 7:30–8:00 A.M. average price for each region. Waste refers to the percent of fishermen who report not selling their catch. Standard errors in parentheses.

there continue to fish in their own catchment zone, about one-third now sell their catch outside their local market. By contrast, all fishermen in regions II and III continue to sell in their local market. However, similar patterns of change in marketing are seen in these other regions once they receive mobile phone service in periods 2 and 3. Overall, the introduction of mobile phones leads to the onset of a significant amount of arbitrage, with 30–40 percent of fishermen on average selling outside their local market on any given day, from an initial situation of near autarky.

Using the same strategy, Table III considers changes in market outcomes. Since prices may vary within a market over the course of the morning, in order to construct a measure of price dispersion we need the prevailing price in each market at a particular point in time. Since in our small sample we do not have a sale at exactly, say, 7:45 A.M. in each market on every day, we instead take the average price for all sales occurring within a time interval; in particular, for most of our analysis we use the average 7:30–8:00 A.M. price, which represents the market closing price (though the results are robust to using alternative times). We assign price based on time of sale rather than time of exchange, i.e., prices for sales via beach auction are assigned to the time of auction, whereas sales via mobile phone are assigned to the time when the sale was arranged, not when the fish were delivered. Provided buyers offer the same price at a point in time in an auction as they would if a fisherman called at that time (even though the fish arrive later), price at time of sale is the most appropriate measure for examining price dispersion since it is the price a fisherman with a phone, who could choose among different markets, would be offered at that time. Finally, a price of zero was assigned when a catch was not sold.

The top panel of Table III shows the max–min price spread, the difference between the highest and lowest 7:30–8:00 A.M. price across the five markets in each of the three regions defined earlier. Prior to the introduction of mobile phones, there were large price differences across markets, with the average max–min spread within a region ranging from 7.6 to 8.2 Rs/kg. However, when phone service was introduced in region I in period 1, the mean spread declined to 1.86 Rs/kg, while declining only slightly in the other two regions. Similarly, when region II received phone service in period 2, the mean spread declined to 1.79 Rs/kg while increasing slightly in region III and declining in region I. Finally, the addition of phones to region III resulted in a similar, though slightly smaller, decline. The second panel shows similar patterns for a more commonly used measure of dispersion, the coefficient of variation (the standard deviation divided by the mean) of the 7:30–8:00 A.M. price across the five markets within each region. In the initial period, price dispersion is high, with the standard deviation within a region 62–69 percent of the mean price in that region. But in each region, once mobile phones are added this measure declines dramatically, to 14 percent or less. In line with the discussion in Section II.B, the fact that price dispersion is so large before mobile phones suggests the net welfare gain from arbitrage is likely to be substantial.

The third panel of the table considers the incidence of waste, measured as the percent of fishing units that do not sell their catch. In the initial period, the incidence of waste is high, with 5 to 8 percent of fishermen unable to sell their catch on an average day. But once mobile phones were introduced to region I, the incidence of waste declined to zero, while declining only slightly in regions II and III. As earlier, similar changes are seen when mobile phones are introduced in regions II and III. The elimination of the significant amounts of waste initially found in the markets suggests not just greater potential welfare gains from arbitrage but also raises the possibility that consumers and producers may both gain on net.

To see these effects even more clearly, Figure IV presents price series for the average 7:30–8:00 A.M. price for one kilogram of sardines in each of the fifteen markets over the sample period, with markets grouped by the regions defined earlier based on when mobile phones were introduced. The graph shows that before any region had mobile phones, the degree of price dispersion across markets within a region on any given day is high, and there are many cases where the price is zero (i.e., waste). However, within a few weeks of mobile phones being introduced in region I, there is a sharp and striking reduction in price dispersion. Prices across markets in the region rarely differ by more than a few rupees per kilogram on any day, compared to cases of as much as 10 Rs/kg prior to the introduction of mobile phones. In addition, the prices in the various markets rise and fall together and the week-to-week variability within each market is much smaller, since catchment zone-specific quantity shocks are now spread across markets via arbitrage. Further, there are no cases of waste in this region after phones are introduced. By contrast, price behavior in regions II and III appears largely unchanged after phones are introduced in region I. However, after mobile phones are introduced in region II, prices again become much less dispersed across markets on any given day, less variable within markets over time, and waste is ultimately eliminated, whereas region III again remains unchanged. Finally, the same pattern holds once region III adds phones. This figure demonstrates clearly the extent to which the changes in price dispersion and waste were large and sudden, with timing that corresponds

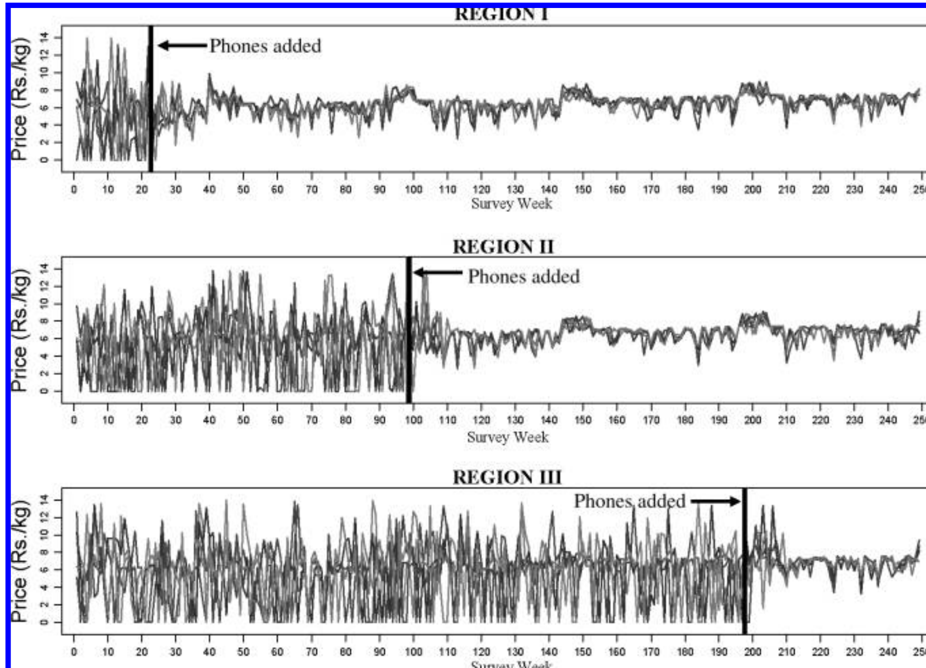

FIGURE IV

Prices and Mobile Phone Service in Kerala

Data from the Kerala Fisherman Survey conducted by the author. The price series represent the average 7:30–8:00 A.M. beach price for average sardines. All prices in 2001 Rs.

closely to the three distinct dates when mobile phone service was introduced in each particular region.

IV. Results: Market Performance

IV.A. Price Dispersion and Waste

Before turning to the full regression specification allowing for separate treatment effects for each region, for ease of presentation we first pool the treatments and estimate,

$$Y_{r,t} = \alpha + \beta_1 \text{Period}_1 + \beta_2 \text{Period}_2 + \beta_3 \text{Period}_3 + \beta_{\text{I}} \text{Region}_{\text{I}} + \beta_{\text{II}} \text{Region}_{\text{II}} + \beta_A \text{Phone}_{r,p} + \gamma Z_{r,t} + \varepsilon_{r,t}$$

where $\text{Phone}_{r,p}$ is a dummy variable equal to one in all periods p in which region r has mobile phone access. Table IV presents the results, which largely mirror those in Table III. The first column shows that the max–min spread across the markets within a region is reduced by 5 Rs/kg on average when mobile phones are added to that region. These changes represent a substantial reduction, since the mean spread prior to the introduction of mobile phones was 7–8 Rs/kg. Column (2) shows the results for the coefficient of variation are again large, with the addition of mobile phone service associated with a reduction of 38 percentage points in the standard deviation relative to the mean. Finally, column (3) shows that waste is reduced by 4.8 percentage points when mobile phones are introduced. Thus, overall, the regression results confirm that the addition of mobile phones was associated with a large and dramatic reduction in price dispersion and waste. Factors affecting the profitability of arbitrage generally have the expected sign for the various market outcomes, with worse wind/sea conditions[20] and higher fuel prices, both of which increase transportation costs, generally associated with greater price dispersion. However, in all cases the effects are small, and we cannot reject the hypothesis that these factors have no effect on the outcomes. The lack of statistical significance may be due to the fact that nearly half the sample consists of period*zone observations where there was no mobile phone coverage and thus no arbitrage, so factors affecting transportation costs would not be expected to influence price dispersion. We therefore estimate regressions where we interact these variables with the indicator for

20. Since wind and sea conditions are highly collinear, we add the two into a single index, varying from zero to six.

TABLE IV
EFFECTS OF MOBILE PHONE SERVICE ON PRICE DISPERSION AND WASTE: POOLED TREATMENTS

	(1) Max–min spread	(2) Coefficient of variation	(3) Percent have waste	(4) Max–min spread	(5) Coefficient of variation	(6) Percent have waste
Phone	−5.0	−.38	−0.048	−5.3	−.41	−0.047
	(0.27)	(0.03)	(0.004)	(2.9)	(0.32)	(0.06)
Region I	−0.92	−.06	−0.007	−0.94	−.06	−0.006
	(0.26)	(0.03)	(0.005)	(0.26)	(0.03)	(0.005)
Region II	−0.46	−.04	−0.011	−0.46	−.04	−0.011
	(0.21)	(0.02)	(0.004)	(0.21)	(0.02)	(0.005)
Period 1	−0.89	−.12	−0.017	−0.84	−.12	−0.016
	(0.29)	(0.04)	(0.008)	(0.29)	(0.03)	(0.008)
Period 2	−1.1	−.17	−0.019	−1.0	−.16	−0.018
	(0.32)	(0.04)	(0.008)	(0.33)	(0.04)	(0.008)
Period 3	−1.2	−.19	−0.022	−1.2	−.19	−0.021
	(0.40)	(0.04)	(0.009)	(0.40)	(0.04)	(0.009)
Fuel cost	0.02	.01	0.001	−0.13	−.02	0.003
	(0.12)	(0.01)	(0.002)	(0.19)	(0.02)	(0.005)
Wind/sea index	0.086	.001	−0.002	−0.03	−.01	−0.003
	(0.051)	(0.004)	(0.002)	(0.06)	(0.01)	(0.003)
Phone*fuel cost				0.25	.026	−0.003
				(0.14)	(0.014)	(0.006)
Phone*wind/sea index				0.19	.021	0.003
				(0.08)	(0.008)	(0.005)
Number of observations	747	747	74,700	747	747	74,700

Data from the Kerala Fisherman Survey conducted by the author. The variable Phone is assigned a value of one for all dates in which a region has mobile phone service available. All prices are in 2001 Rs. Standard errors, clustered at the village level for columns (3) and (6), in parentheses.

whether the region had mobile phones. In columns (4) and (5), both interaction terms are statistically significant for the max–min price spread and the coefficient of variation, with the expected signs; higher fuel costs and worse wind/sea conditions increase price dispersion when there is arbitrage in a region. And, as expected, we cannot reject the hypothesis that these variables have no effect on dispersion when mobile phones are not available in a region. In column (6), the wind/sea and fuel interaction terms still have no effect on waste since there is no waste after mobile phones are introduced.

As stated earlier, we can exploit the variation in the timing of introduction of mobile phones across the three regions by estimating regressions with separate treatment effects. Table V presents the estimated effects of mobile phones on the market outcomes for each

TABLE V
ESTIMATED EFFECTS OF MOBILE PHONES ON MARKET OUTCOMES: SEPARATE TREATMENTS

	Max–min spread	Coefficient of variation	Waste
Estimated effects of adding phones to region I			
(a) Using region II as the control group	−4.8	−.46	−0.064
$(Y_{I,1} - Y_{I,0}) - (Y_{II,1} - Y_{II,0}) = \beta_{RI\_P1} - \beta_{RII\_P1}$	(0.68)	(0.07)	(0.005)
(b) Using region III as the control group	−4.8	−.42	−0.060
$(Y_{I,1} - Y_{I,0}) - (Y_{III,1} - Y_{III,0}) = \beta_{RI\_P1}$	(0.68)	(0.07)	(0.005)
Estimated effects of adding phones to region II			
(c) Using region I as the control group	−5.8	−.39	−0.039
$(Y_{II,2} - Y_{I,1}) - (Y_{I,2} - Y_{I,1}) = \beta_{RII\_P2} - \beta_{RII\_P1} - \beta_{RI\_P2} + \beta_{RI\_P1}$	(0.43)	(0.05)	(0.003)
(d) Using region III as the control group	−4.9	−.36	−0.038
$(Y_{II,2} - Y_{II,1}) - (Y_{III,2} - Y_{III,1}) = \beta_{RII\_P2} - \beta_{RII\_P1}$	(0.43)	(0.05)	(0.003)
Estimated effects of adding phones to region III			
(e) Using region I as the control group	−4.9	−.38	−0.055
$(Y_{III,3} - Y_{III,2}) - (Y_{I,3} - Y_{I,2}) = \beta_{RI\_P2} - \beta_{RI\_P3}$	(0.48)	(0.05)	(0.004)
(f) Using region II as the control group	−4.7	−.35	−0.054
$(Y_{III,3} - Y_{III,2}) - (Y_{II,3} - Y_{II,2}) = \beta_{RII\_P2} - \beta_{RII\_P3}$	(0.48)	(0.05)	(0.004)

Data from the Kerala Fisherman Survey conducted by the author. The table reports the estimated effects of mobile phones on market outcomes separately for each of the three regions using the combinations of coefficients listed in small type, based on the full regression results in columns (1)–(3) in Table X. Standard errors, clustered at the village level for column (3), in parentheses. All prices in 2001 Rs.

of the three regions, which, in most cases, are a combination of the coefficients from the full regressions (presented in the Table X). The results are broadly similar to those for the pooled regressions. Estimators (1) and (2), the impact on region I of adding phones between periods 0 and 1, reveal that the max–min spread across markets was reduced by 4.8 Rs/kg when compared to either region II or III. For region II (estimators (3) and (4)), the effects are slightly larger, 4.9 and 5.8 Rs/kg, than for region I; using region I as a control group results in a higher estimate than using region III, but we cannot reject the hypothesis that the two effects are equal. Finally, the effects in region III are similar to those in region I. And as with the other two regions, we cannot reject the hypothesis that the estimated effects are equal for the two comparison groups. Overall, the estimates show some variation in the magnitude of the effects across the regions, ranging from 4.7 to 5.8 Rs/kg for the max–min price spread, 35 to 46 percentage points for the coefficient of variation and 3.8 to 6.4 percentage points for waste. However, for both the max–

min spread and the coefficient of variation, we cannot reject the hypothesis that the effects are equal for all pairwise comparisons of region*control group; for waste, the effects are statistically significantly smaller for region II than for either regions I or III due to the fact that waste was lowest there prior to the introduction of mobile phones. Overall, the results confirm that the introduction of mobile phones was associated with a large and dramatic reduction in price dispersion and waste, with broadly similar effects across the regions.

IV.B. The Identifying Assumption

The identifying assumption for the empirical strategy is that, had it not been for the introduction of mobile phone service, there would have been no differential changes in the market outcomes across these regions over this period. We discuss three potential areas of concern. First, in attributing all the differential changes in market outcomes to the addition of mobile phones, we are assuming that there were no pre-existing differential trends in market outcomes across these regions and that no other factors that could also have influenced these outcomes changed differentially across the regions. Figure IV revealed that the changes in market outcomes were sharp and sudden and correspond closely to the distinct points of introduction of mobile phone service in each region. And the fact that no other large changes in price dispersion are observed except around these three distinct points suggests that differential changes in other factors are unlikely to have caused any significant fraction of the changes in price behavior attributed to mobile phones, since it is very unlikely that these other factors would have differentially changed at the same three specific dates at which each region received mobile phone service, but not at any other time. The sharp and sudden changes also make it unlikely that differential trends across the regions explain much of the differential changes in outcomes (common trends are controlled for). More formally, in regressions for the market outcomes using only the observations before mobile phones were available in any region (period 0) and including a linear time trend, region indicators, and time*region interactions, both the trend and interaction terms are small and not statistically significantly different from zero (results not shown). The same holds for regressions using only regions II and III, with data from periods 0 and 1 (before either region had mobile phones).[21]

21. However, we cannot rule out differential trends arising only around the same time mobile phones were introduced in each region.

A second concern is that the timing of service across the regions was nonrandom.[22] According to the mobile phone providers, the order of placement of service was determined by the size of the potential market, i.e., the population of the main city in each region. While the effects of fixed factors that differ across regions like population size are controlled for in the regressions, and while we saw no evidence of differential trends across the regions, we may be concerned that the timing of introduction of service in a particular region was delayed or sped up in response to other factors that could also affect market outcomes. For example, rapid economic growth could have caused firms to speed up the delivery of mobile phone service because of the potential increased demand and separately could also have improved fish market outcomes, such as by increasing overall demand and reducing waste. This would result in a close correspondence between the introduction of mobile phones and changes in market outcomes, without the former having caused the latter. As with the first concern, from Figure IV alone we consider this possibility unlikely, since we do not see any differential trends, or any large changes in the price series at any points in time other than when phones were introduced, and it is unlikely that changes in these other factors happened to occur at these three specific points in time (but no other time). Further, since mobile phone service takes a long time to set up, if the timing of service was responding to changes in factors (like economic growth) that were already beginning to improve market outcomes, we would expect to observe changes in these outcomes before phones are introduced, whereas Figure IV (and regressions using month instead of period indicators (not shown)) shows that outcomes improved only after phones were introduced.[23]

The third concern with the identification strategy is the possibility of migration of fishing or marketing activities in response to the addition of mobile phones. For example, when phones are introduced in region I, some fishermen in region II may begin fishing and/or marketing in region I (though such migration might work against our results, for example, by

22. There is not a concern, however, regarding nonrandom placement since the initial plan of mobile phone providers and the ultimate outcome was to cover the entire coast, not just select areas.

23. Though we have to assume that phone companies did not accurately forecast in advance differential changes in these other factors, there is no evidence that there were any specific periods of large, sharp differential changes in, say, economic growth in these regions over this period, much less predictable changes.

increasing supply and therefore waste in region I). However, Table II reveals that both before and after mobile phones almost all fishermen fished within their own catchment zone, with no change surrounding the introduction of mobile phones. Further, the table reveals that after phones are introduced in region I, all fishermen in regions II and III still sell in their local market; similarly, all fishermen in region III sell in their local market even after phones are introduced in region II.

IV.C. Alternative Explanations of the Results

A final concern is whether the introduction of mobile phones had effects other than purely providing price information to potential arbitrageurs that could also influence market outcomes. While we would still identify the effects of adding mobile phones on market outcomes, we could not interpret the results as (solely) evidence of the effects of enhanced arbitrage resulting from greater access to information. We consider six possibilities. The first is whether mobile phones affected entry and exit, such as in response to an increase in the profitability of fishing. Differential changes in the number of craft fishing could, in turn, affect the supply to markets and, thus, market outcomes (though in some cases this would work counter to our results; for example greater entry would be expected to increase the amount of waste). The bottom panel of Table II provides data on the average number of fishing units per landing, from a census conducted each September by the author from 1996 to 2001. Over the five-year period of the study, there was a moderate amount of entry, with each landing adding, on average, three to six units, relative to the base of fifty-three to eighty-three. However, looking across the table, there is no correlation between changes in the number of units and the introduction of mobile phones in a region: upon adding mobile phones, region I added the same number of units as region III but three fewer than region II; region II added one more than region I and two more than region II; and region III added two more than region II, but two fewer than region I. High capital investment or the specific knowledge required for fishing may ultimately limit entry; further, fishing is largely conducted by members of only a few specific subcastes.

A related concern is whether mobile phones affected the quantity or variability of fishermen's catch. For example, fishermen could diversify fishing location and use mobile phones to inform each other of places with the best catch, which could increase total catch and/or reduce supply variability within (and across) catchment zones and thus reduce price dispersion and variability.[24] Alternatively, fishermen might either lengthen or shorten their fishing time in response to learning market prices while at sea, either staying out to catch more fish when they learn prices are high or coming in early when they learn that prices are low. Under such behavior, the variability of catch across and within markets would be reduced, even if there were no arbitrage. In the first column of Table VI, we show results from pooled treatment regressions like those above, where the dependent variable is the amount of fish caught (using fisherman-level data). The coefficient on the variable indicating the region has phones is negative, but very small and not statistically significantly different from zero, indicating that the introduction of mobile phones is not associated with a net change in the average catch of fishermen. However, this could be the result of offsetting positive and negative supply responses (cutting back catch when price is low and increasing catch when price is high). Therefore, we construct the coefficient of variation of the estimated total catch in the five catchment zones within each region based on fishermen's reports of approximate fishing location. In column (2) of Table VI, there is no evidence that the variability of catch declined in response to the introduction of mobile phones. The reduction in price dispersion across markets is therefore not attributable to a reduction in catch dispersion across markets.

A third concern is that if mobile phones lead to increases in wealth in those areas with coverage, such as through improving the performance of other economic sectors, there could be shocks to the demand for sardines that would exactly correspond to the introduction of mobile phone service in each region. It is possible, for example, that holding supply variability constant, a change in wealth could shift demand in such a way that supply varies along a flatter part of the demand curve, reducing price dispersion or variability. Or by increasing aggregate demand, increases in wealth could lead to reductions in waste. While we do not have high frequency consumption data over this period to test this hypothesis, we did

24. Though in interviews, we found no evidence of such behavior. The gains to diversification increase with distance, but so does the time (and cost) required to reach one spot from another, so the fish may have moved away between when one fisherman calls and the other can arrive. In addition, it is difficult to pinpoint and communicate exact location while at sea. Finally, catch is to an extent rival, so those with a good catch have an incentive to lie, and catch is hard to monitor, especially when fishermen sell in different markets.

TABLE VI
TESTING ALTERNATIVE EXPLANATIONS

	Supply		"Maximum dispersion" prices		Predicted prices		
	(1) Quantity (kilogram)	(2) Coefficient of variation	(3) Max–min spread	(4) Coefficient of variation	(5) Max–min spread	(6) Coefficient of variation	(7) Waste
Phone	−1.4	−.02	−4.5	−.34	−4.4	−.31	−0.048
	(9.2)	(0.04)	(0.34)	(0.04)	(2.9)	(0.30)	(0.06)
Region I	33	−.08	−0.77	−.06	−0.91	−.06	−0.006
	(8.0)	(0.04)	(0.31)	(0.04)	(0.28)	(0.02)	(0.005)
Region II	17	−.06	−0.48	−.03	−0.43	−.06	−0.011
	(0.21)	(0.03)	(0.23)	(0.02)	(0.23)	(0.03)	(0.005)
Period 1	−15	−.002	−0.80	−.08	−0.79	−.11	−0.016
	(14)	(0.04)	(0.29)	(0.03)	(0.24)	(0.04)	(0.008)
Period 2	−28	.05	−0.98	−.13	−1.1	−.14	−0.018
	(18)	(0.05)	(0.31)	(0.04)	(0.31)	(0.04)	(0.008)
Period 3	−20	.03	−1.1	−.17	−0.98	−.21	−0.021
	(20)	(0.06)	(0.38)	(0.04)	(0.39)	(0.03)	(0.009)
Number of observations	74,700	747	747	747	747	747	74,700

Data from the Kerala Fisherman Survey conducted by the author. The variable Phone is assigned a value of one for all dates in which a region has mobile phone service available. All prices are in 2001 Rs. Column (1) uses fisherman-level observations on catch for the dependent variable while column (2) uses the coefficient of variation of estimated total catch across markets within a region. Columns (3) and (4), "Maximum dispersion" prices, estimate the pooled treatment regressions using the highest values of the coefficient of variation and max–min spread observed during a given market day. Columns (5)–(7) use prices predicted from pre-phone market demand curves for post-phone periods rather than actual prices. Standard errors, clustered at the village level for columns (1) and (7), in parentheses.

conduct annual household surveys from 1996 to 2001 at fifteen inland, nonfishing towns, each served by one of the beach markets in our survey.[25] Within each town, we randomly chose twenty households and gathered detailed information on income, consumption, and expenditures. Estimating sardine demand curves with these data, we find that the income elasticity of demand is 0.12, with a standard error of 0.07. This elasticity is positive but small, suggesting that unless the wealth effects of mobile phones were very large, it is unlikely that, say, much of the reduction in waste observed is due to increased demand. We can also test whether wealth changes the price elasticity of demand for sardines (which, in turn, might affect price dispersion) by dividing households into high and low wealth groups (above vs. below the sample median). The estimated price elasticities are very similar for the two groups; −0.16 (standard error 0.09) for wealthier households and −0.23 (0.14) for poorer households, and we cannot reject that they are equal. Changes in wealth would therefore be unlikely in themselves to have had a large effect in reducing price dispersion unless the changes in wealth were very large.

A fourth alternate explanation of the results is that changes in the timing of transactions associated with sales via mobile phone may introduce a systematic bias in our comparisons of price dispersion over time. For example, suppose buyers start every day by offering an average price based on the mean expected supply for that time of year, and then adjust up or down later in the day as the catches of arriving fishermen provide new information. In this case, since mobile phones give information about supply far in advance of the fish arriving at the market, it may be that phones simply allow the adjustment to take place earlier in the day, with net dispersion unchanged.[26] To explore this issue, we estimate the pooled treatment regressions using the maximum values of the coefficient of variation and max–min spread observed at any time (thirty-minute interval) during the day. Columns (3) and (4) of Table VI show that the estimated effects are only slightly smaller than the original estimates (columns (1) and (2) of Table IV) when this adjustment is

25. However, these towns were chosen because their proximity to roads made it feasible to survey them on a regular basis (for a weekly consumer price survey, discussed below), and they are therefore wealthier and have better infrastructure on average than other towns or villages in the region.

26. We note that, however, the measurement of waste does not suffer from the same timing issue because we measure any occurrence of waste in our sample throughout the day, not at a particular point in time.

made; this is largely because price dispersion varies very little during the market.

A fifth concern is whether price dispersion was reduced simply because mobile phones enabled greater price collusion across markets, on the part of either fishermen or buyers, by directly facilitating communication and coordination.[27] In interviews, fishermen, buyers, and NGOs in these regions all indicate that the markets have always been very competitive, with no evidence of collusion or price fixing either before or after mobile phones. This is attributed largely to the fact that there is a large number of small agents on both sides of the market, making collusion difficult to sustain. And, of course, we can rule out that all of the reduction in price dispersion is due to greater price fixing across markets since then we would not expect to see fishermen selling outside their local markets (as observed in Table II). However, unfortunately, the hypothesis that at least some collusive behaviors changed cannot be tested directly, though later we discuss a limited approach.

Finally, sales via mobile phone may also have changed the contracting environment, for example, providing insurance for buyers against ending the day without purchasing any fish or for fishermen against not being able to sell their fish. For example, before mobile phones, some very risk-averse buyers may have paid a premium to ensure supply (especially on days when the first fishermen arriving indicated a low catch), or some risk-averse fishermen may have accepted lower prices to ensure a sale. If the degree of risk aversion varied across markets, or if such "insurance pricing" pushes prices towards the extremes, it could affect price dispersion. Mobile phones might therefore reduce dispersion simply by reducing uncertainty by allowing buyers and sellers to call and learn about the catch early in the day, minimizing the need for such pricing behavior. As earlier, we can rule out the hypothesis that all of the changes in price dispersion are attributable to changes in insurance pricing since we would then not observe arbitrage as in Table II. And in extensive focus group and individual interviews, neither buyers nor fishermen report any such behavior. Unfortunately, however, it is not possible to test this hypothesis more formally.

While we were unable to directly rule out the previous two

27. Mobile phones could also make collusion more difficult to sustain since more transactions are conducted in private over the phone rather than through auctions on the beach that are easily monitored by others.

concerns, we can provide a rough "plausibility check" on whether the changes in market outcomes would have been predicted based solely on the amount of arbitrage observed once phones were in place. In particular, we first estimate beach-level demand curves using only observations in each region before mobile phones were in place, relating the mean 7:30–8:00 A.M. price to estimates of total quantity delivered to the market.[28] Then using data on catch and market of sale from dates after mobile phones are introduced, we estimate the quantity delivered to each market and predict the 7:30–8:00 A.M. prices that would prevail under the pre-phone demand curves. Finally, we use these results to generate predicted measures of price dispersion for post-phone periods.[29] Again, this approach is intended primarily to provide a check for whether the changes in outcomes are consistent with the increased amount of arbitrage observed. However, it also indirectly provides some rudimentary bounds on the extent to which changes in other factors caused by mobile phones can explain the changes in market outcomes; if price collusion or insurance pricing were significant factors in determining price dispersion, and these behaviors changed significantly when mobile phones were introduced, we would expect quantity to be a poor predictor of post-phone outcomes when predicted off of pre-phone demand curves.

Applying this approach, we find that there is a high correlation between the predicted and actual max–min price spread, coefficient of variation, and waste in post-phone periods; regressing the predicted measures on actual measures yields R^2 of .83 or above for all three measures. And in post-phone dates, the predicted max–min price spread differs from the observed spread by more than 1 Rs/kg in only 6 percent of region*date cases,[30] and we accurately predict that waste would fall to zero under the

28. For a more flexible approach, we actually estimate the weighted average price at 100 points for quantity using a kernel smoother with a bandwidth of 0.1 and a quartic kernel.

29. One concern with this approach is that demand may have changed over time. Another is that while we have representative samples of fishermen in each village, after mobile phones are introduced, the sample of fishermen who visit a market on a particular day is not necessarily a representative sample of all fishermen who visited that market. While we will observe fishermen from our high catch markets visiting non-sample markets, we will not observe fishermen from non-sample markets visiting our low-catch sample markets. Thus, we will more accurately estimate quantity when there is a high catch in the zone near a market than when there is a low catch. Thus, we are likely to predict higher levels of price dispersion than if we could directly measure the amount of fish arriving at the market.

30. As expected, for most such cases we overpredict dispersion.

observed levels of arbitrage. Further, in columns (5)–(7) of Table VI, we show regression results where the dependent variables are constructed using the predicted values for market outcomes for post-phone dates and actual outcomes for pre-phone dates. The results are very similar to (though slightly smaller than) those using only observed price dispersion in Table IV; the max–min spread is reduced by 4.4 Rs/kg, the coefficient of variation is reduced by .31, and waste is reduced by 4.8 percentage points. Thus, on the basis of the amount of arbitrage observed alone, we predict similar reductions in price dispersion as those actually observed. Again, while this approach cannot rule out the possibility of changes in other factors, it does show that the changes in market outcomes are highly consistent with, and well predicted solely by, the amount of arbitrage observed. Coupled with the evidence from interviews with fishermen and buyers suggesting neither collusion nor insurance pricing were significant factors before or after mobile phones, this suggests that to the extent these other factors are relevant, they can likely explain very little of the total change in outcomes observed.[31]

IV.D. The Law of One Price

Provided there are no other barriers to arbitrage, sardine prices should not differ between any two markets by more than the cost of transportation between them. We can provide a direct, though approximate, test of the LOP. The primary variable cost influencing arbitrage is fuel, which is primarily affected by distance, wind and sea conditions, and the amount of fish being transported. On select days between May and September of 2003 we equipped two fishing boats with Global Positioning System devices to calculate distance traveled and gauges to monitor fuel use. These trials provided variation in wind and sea conditions and catch sizes, which allows us to estimate fuel use per distance

31. However, this does not rule out the possibility that while phones enabled arbitrage, it was not solely through providing price information. For example, the initial lack of arbitrage may have been due to collusion, such as buyers punishing fishermen who sold non-locally or fishermen punishing buyers purchasing from non-local fishermen, but otherwise not colluding over price. However, we consider this possibility unlikely. First, fishermen reported no such constraints on where they could sell, and buyers reported no constraints on who they could buy from, either before or after mobile phones. Second, it is unclear if mobile phones would reduce the ability to sustain such collusion since, even though sales via phone are private, the fish must still be delivered to the buyer on the beach, so transactions involving non-locals can still be observed. Finally, it seems unlikely that such collusion would be sustained by a group but that that collusion would not also extend to pricing.

TABLE VII
VIOLATIONS OF THE LAW OF ONE PRICE

	Period 0 (pre-phone)	Period 1 (region I has phones)	Period 2 (region II has phones)	Period 3 (region III has phones)
Overall				
Region I	0.54	0.03	0.04	0.03
Region II	0.57	0.55	0.06	0.05
Region III	0.60	0.58	0.58	0.08
With time + depreciation				
Region I	0.50	0.01	0.02	0.02
Region II	0.53	0.52	0.03	0.03
Region III	0.57	0.55	0.54	0.05
All markets combined				
Without time + depreciation	0.47	0.35	0.20	0.05
With time + depreciation	0.44	0.31	0.16	0.03

Data from the Kerala Fisherman Survey conducted by the author. In the top two panels, the figures represent the average percent of unique market-pairs among the five markets in a given region for which the 7:30–8:00 A.M. average price differences differ by more than the estimated transportation costs between the two markets on a given day. For the bottom panel, the figures are for the unique market pairs among all fifteen markets in the sample.

traveled for various combinations of these factors. We then construct an estimate of the cost of traveling between each pair of markets for each survey date, using data on the cost of fuel in the source market and the wind and sea conditions for a hypothetical boat carrying the average catch received on that day in the source catchment zone. Using these estimates, for example, a twenty-eight-foot boat carrying 300 kilograms of sardines thirty kilometers with no wind and calm sea conditions would consume an additional thirty liters of fuel. Thus, on a day with these conditions when fuel costs 15 Rs/liter, the fuel cost of arbitrage over this distance is 450 Rs, so the price for sardines in two markets thirty kilometers apart should not differ by more than 1.5 Rs/kg.

For all pairs of markets, Table VII shows the percent of market-pair*day observations with 7:30–8:00 A.M. price differentials that exceed the estimated transportation cost between the markets. The top two panels of the table consider only the ten unique pairs of the five markets within each of the three regions. In the initial period, 54–60 percent of market-pair*day combinations had price differentials that exceeded estimated travel costs, i.e., violations of the LOP. Including estimates of the value of time and depreciation associated with arbitrage reduces estimated violations to 50–57 percent.[32] Following the introduction of mobile phone service, in each region the LOP was violated in only 3–8 percent of cases without accounting for time and depreciation and 1–5 percent when including these costs. The bottom panel considers the combinations of all fifteen markets rather than just testing within regions. Initially, the LOP is violated in 44–47 percent of cases, depending on whether time and depreciation are included. Once mobile phones are introduced in region I, this is reduced to 31–35 percent. Adding phones in region II reduces violations to 16–20 percent, and adding phones to region III reduces it to 3–5 percent. Thus, while violations can still be found, markets arrive at a very close approximation to the LOP. The overall change is striking; from an initial situation where towns operated in near autarky, with all fish caught and sold locally and excess price dispersion was the norm, the introduction of mobile phones results in nearly perfect exploitation of profitable arbitrage opportunities.[33]

V. Welfare Effects

The results so far suggest there are likely to be net welfare gains associated with the introduction of mobile phones due to the more efficient allocation of fish, i.e, reallocating them to where they are more highly valued on the margin, including the elimination of waste. As shown earlier, how the gain is shared between producers and consumers and whether each group gains or loses on net is ambiguous. We take a reduced-form approach and provide simple estimates of the welfare changes. For fishermen, changes in profits are an appropriate measure of changes in welfare since fixed costs do not change and supply appears to be

32. The survey gathered data on when boats left and returned to their home port, so we can estimate time spent at sea, which we can value at the market wage. For depreciation, the typical outboard motor costs about 100,000 Rs and has a life span of 3,500 operating hours. Fishing craft, while expensive, have a long operational life (ten to fifteen years) and depreciate due to age more than use. Nets do not depreciate with arbitrage since they are not exposed to any additional wear while being transported on the boat. Thus we assume that both net and craft depreciation are negligible. Overall, then, depreciation from an additional hour of operation is valued at 29 Rs.

33. Though in principle, a fully-informed planner who could assign all fishermen across markets at the end of the day might be able to achieve a better allocation with smaller price differences across markets and greater total welfare. (For example, there may be cases where a fisherman from market A visits a market close to market B and later in the day a fisherman from market B visits a market close to market A; if all catches were known, a planner could ensure fishermen engage in arbitrage with the markets nearest to them.)

relatively inelastic (Table VI). In addition, changes in price variability are unlikely to directly affect fishermen's welfare appreciably since the variability is at the daily level and is therefore fairly easily smoothed over short intervals.[34] The change in profits will arise through changes in price and quantity sold and the costs associated both with mobile phones and increased travel due to arbitrage. Table VIII shows the effects of the introduction of mobile phones for the pooled treatments, and Table IX shows the estimated effects from the regressions with separate treatments (full results are in the Table X). The first column of Table VIII shows that mobile phones, on average, increased quantity sold by twenty-three kilograms per day, resulting from the decline in waste. Table IX shows that the effects are similar across the regions, though slightly larger in region I due to the greater pre-phone amount of waste. By contrast, the average price received decreased by .05 Rs/kg, though the overall effect is only marginally statistically significant. There is some variation in the change in price across the three regions, with some featuring price increases and some decreases, though the only statistically significant effects are a price increase of .16 Rs/kg in region I (relative to region III) and a decrease of .10 Rs/kg in region II (relative to region I). In column (3) we consider the change in the price among fish sold (i.e., excluding the pre-phone zeroes for unsold fish). Now, the change in average price received is negative and statistically significant (likely due in part to what is effectively an increase in supply of fish sold due to the reduction in waste). The price declined by .44 Rs/kg on average in the pooled treatment, or about 5 percent, with the largest declines in region III. Overall, revenue increased by 205 Rs, with the smallest effects in region III, while costs (including mobile phone use) increased, on average, by 72 Rs per day once mobile phones were introduced (though the effects are again smaller in region III). Column (5) shows the net effect of these changes is an increase in average profits of 133 Rs per day; this is a large gain, comprising about a 9 percent increase.[35] It is also important to keep in mind

34. However, we note that reduced price variability increases profit variability, since with spatial correlation in catches but no arbitrage, a low catch by a fisherman is usually met with a high price, and vice versa for a high catch. Increased arbitrage weakens the negative correlation between own catch and price, increasing profit variability.

35. Note, boats are often owned by several fishermen who split the profits, so the mean monthly profit per boat is greater than the average monthly income in this region.

TABLE VIII
EFFECTS OF MOBILE PHONES ON PRODUCERS AND CONSUMERS: POOLED TREATMENTS

	(1) Quantity sold	(2) Price	(3) Price (if >0)	(4) Revenue	(5) Costs	(6) Profits	(7) Profit users	(8) Profit nonuser	(9) Consumer price	(10) Consumer surplus
Phone	23	−.05	−.44	205	72	133	184	97	−.39	.14
	(8.4)	(0.03)	(0.03)	(62)	(5.6)	(60)	(90)	(47)	(0.22)	(0.04)
Region I	36	.25	−.19	370	3.7	367	458	306	.51	−.11
	(6.6)	(0.03)	(0.03)	(56)	(4.9)	(54)	(77)	(44)	(30)	(0.03)
Region II	22	.03	−.07	173	3.3	170	204	130	.38	−.03
	(5.2)	(0.02)	(0.02)	(42)	(3.0)	(40)	(57)	(35)	(0.27)	(0.02)
Period 1	−5.3	.48	.36	66	7.6	58	63	61	.22	−.16
	(10)	(0.03)	(0.03)	(59)	(4.2)	(58)	(94)	(43)	(0.05)	(0.04)
Period 2	−17	.64	.51	34	2.3	32	−6.3	62	.65	−.30
	(14)	(0.04)	(0.03)	(80)	(3.7)	(80)	(122)	(57)	(0.27)	(0.05)
Period 3	−7.8	1.0	.84	215	16	200	212	189	.81	−.48
	(16)	(0.05)	(0.04)	(99)	(6.0)	(97)	(145)	(74)	(0.35)	(0.05)
Observations	74,700	74,700	73,335	74,700	74,700	74,700	41,012	33,688	3,735	3,735

The data in columns (1)–(8) are from the Kerala Fisherman Survey conducted by the author. Columns (9) and (10) are from the annual household surveys conducted by the author. Standard errors, clustered at the village level, in parentheses. All prices in 2001 Rs.

TABLE IX
EFFECTS OF MOBILE PHONES ON PRODUCERS AND CONSUMERS: SEPARATE TREATMENTS

	(1) Quantity sold	(2) Price	(3) Price (if >0)	(4) Revenue	(5) Costs	(6) Profits	(7) Consumer price
Estimated effects of adding phones to region I							
(a) Using region II as the control group	35	.11	−.46	251	100	151	−.43
$(Y_{I,1} - Y_{I,0}) - (Y_{II,1} - Y_{II,0}) = \beta_{RI\_P1} - \beta_{RII\_P1}$	(7.6)	(0.08)	(0.07)	(60)	(11)	(57)	(0.21)
(b) Using region III as the control group	25	.16	−.41	199	93	106	−.41
$(Y_{I,1} - Y_{I,0}) - (Y_{III,1} - Y_{III,0}) = \beta_{RI\_P1}$	(7.7)	(0.07)	(0.06)	(62)	(11)	(56)	(0.22)
Estimated effects of adding phones to region II							
(c) Using region I as the control group	22	−.10	−.40	222	92	130	−.39
$(Y_{II,2} - Y_{I,1}) - (Y_{I,2} - Y_{I,1}) = \beta_{RII\_P2} - \beta_{RII\_P1} - \beta_{RI\_P2} + \beta_{RI\_P1}$	(4.8)	(0.05)	(0.04)	(38)	(6.8)	(35)	(0.22)
(d) Using region III as the control group	21	−.06	−.37	248	79	169	−.38
$(Y_{II,2} - Y_{II,1}) - (Y_{III,2} - Y_{III,1}) = \beta_{RII\_P2} - \beta_{RII\_P1}$	(4.9)	(0.05)	(0.05)	(40)	(6.9)	(36)	(0.22)
Estimated effects of adding phones to region III							
(e) Using region I as the control group	24	−.07	−.53	169	40	129	−.38
$(Y_{III,3} - Y_{III,2}) - (Y_{I,3} - Y_{I,2}) = \beta_{RI\_P2} - \beta_{RI\_P3}$	(5.4)	(0.05)	(0.04)	(43)	(7.7)	(40)	(0.21)
(f) Using region II as the control group	21	−.05	−.50	150	51	99	−.38
$(Y_{III,3} - Y_{III,2}) - (Y_{II,3} - Y_{II,2}) = \beta_{RII\_P2} - \beta_{RII\_P3}$	(5.5)	(0.06)	(0.05)	(44)	(7.8)	(40)	(0.20)

The data in columns (1)–(6) are from the Kerala Fisherman Survey conducted by the author. Column (7) is from the annual household surveys conducted by the author. The table reports the estimated effects of mobile phone use on market outcomes separately for each of the three regions using the combinations of coefficients listed in small type, based on the full regression results in columns (4)–(9) in the Table X. Standard errors, clustered at the village level, in parentheses. All prices in 2001 Rs.

that rather than a one-time gain, the increase in profits represents a persistent change, due to the improved functioning of the market. Table IX reveals that the gains were positive and statistically significant for all three regions, though smallest for region III, especially when region II is used as the control group.

In columns (7) and (8) of Table VIII, we examine the changes in profits separately for mobile phone users versus nonusers. Boats using mobile phones, on average, increased profits by 184 Rs per day, compared to 97 Rs for nonusers. Boats with mobile phones gained more (nearly twice as much) in part because they are, on average, larger boats and thus catch more fish and because they are more likely to be able to profitably exploit the small remaining arbitrage opportunities (as revealed in Table VII where some violations of the LOP still exist). However, phone users had a clear positive externality on nonusers, who will, for example, no longer have days with unsold fish because boats with phones will switch to other markets when the local catch is high. We can also use these results to examine the value of mobile phones as an investment for fishermen. While costs varied over the course of the survey, we can approximate the cost of a handset at 5,000 Rs and the monthly costs of use at 500 Rs. The net increase of 184 Rs per day in profits for phone users would then more than cover the costs of the phone in less than two months (assuming twenty-four days of fishing per month), making phones a worthwhile investment. In addition, there is no incentive to free ride; the additional 87 Rs per day of profit gained by users relative to nonusers would offset the costs of owning and operating the phone in just over three months. Thus, phones were a profitable investment for the fishermen who adopted them.

Turning to consumers, we begin by examining the change in consumer retail price. As part of this study we conducted weekly market price surveys on the same days as the fishing unit survey at the same fifteen inland, nonfishing towns used for the household survey described earlier. For this survey, enumerators gathered data on prices for various food items, including sardines, at retail shops. The last column of Table VIII shows that, on average, the introduction of mobile phones was associated with a .39 Rs/kg reduction in price, which is just under 4 percent relative to the base of about 11 Rs/kg; Table IX shows the effect is similar across the three regions. The magnitude of the effect is modest, though fish are typically consumed daily and thus constitute a moderate share of household food expenditures; further, as with profits, the effects are a persistent change rather than a one-period decline.[36]

The change in consumer welfare is, of course, more than just the change in price. While we lack the data to undertake a full welfare analysis for consumers, we provide a rough approximation.[37] Using the annual household surveys, we first estimate the consumer demand curve for sardines, with separate curves for pre- versus post-mobile-phone introduction. Then from the weekly retail market price data, we construct CS as the area under the demand curve and above the price line in each of the markets for each day of the survey. We then run regressions like those above, using the generated CS for each market*week observation as the dependent variable. While the change in CS has well-known problems as a measure of welfare changes associated with price changes,[38] a benefit to this reduced-form approach is that it captures the consumer gains or losses from reduced price variability, such as smoother consumption or fewer opportunities to engage in intertemporal substitution. Such factors are reflected in the equilibrium demand curves, and thus any welfare changes due to these other effects is accounted for by estimating CS off of separate demand curves before and after price variability is reduced.[39]

Using the pooled treatment regression,[40] the last column of

36. However, the change in the average market clearing price, which is what is measured by the retail price survey, is not the same as the change in the average price paid by consumers; in general, the latter will typically be less than the former (and may even have the opposite sign). Unfortunately, we do not have high frequency consumption data at the household level, so we cannot estimate the change in the purchase price of fish.

37. Newbery and Stiglitz [1981] and Wright and Williams [1988] provide frameworks for analyzing the welfare effects of price stabilization, but, unfortunately, these frameworks cannot be directly applied to the current case.

38. Using CS to compare welfare assumes a constant marginal utility of income or zero wealth effects of price changes (so Marshallian demand can be used in place of Hicksian compensated demand). However, Willig [1976] showed that the error in using the change in CS instead of equivalent or compensating variation for measuring the welfare effects of price changes is small, especially when wealth elasticities in the demand for that good are small (which was shown to be the case here). Further, since we are examining a reduction in price variability, some errors will be offsetting; the errors caused by the wealth effects of comparing a high to an average price will be the opposite of the errors from comparing a low to an average price. Finally, Wright and Williams [1988] show that the change in CS is a good approximation to the change in welfare associated with price stabilization provided the budget share of the good is small (<10 percent, as it is in the present case).

39. Though some consumers may be worse off even if consumers gain on average; for example, consumers with the greatest willingness to wait for low prices lose because very low prices no longer occur.

40. We do not estimate regressions with separate treatments because our small sample only allows us to estimate a single demand curve for all three regions.

Table VIII shows that consumer surplus in sardines increased by .14 Rs per person per day, which is 6 percent of the average pre-phone CS for sardines (2.27 Rs per person per day). Thus, consumers gain as a result of the introduction of mobile phones, and the gain is economically significant as a fraction of the initial CS in sardines. Though it should be noted that even multiplied by thirty (under the assumption that fish are consumed daily by most households), when compared to the average monthly expenditure per capita of 678 Rs (estimated from the household survey), the gain is very small (though if similar gains arise in the market for other commonly consumed goods, the overall consumer gains relative to expenditure might be larger).

VI. Conclusion

We find that the addition of mobile phones reduced price dispersion and waste and increased fishermen's profits and consumer welfare. These results demonstrate the importance of information for the functioning of markets and the value of well-functioning markets; information makes markets work, and markets improve welfare. And it is again worth emphasizing that the results represent persistent rather then one-time gains since market functioning should be permanently enhanced by the availability of mobile phones. As mentioned earlier, information technologies are often considered a low priority for developing countries relative to needs in areas such as health and education. However, not only can such technologies increase earnings, but those increased earnings (or increased purchasing power, due to reduced consumer prices), in turn, can be expected to lead to improvements in health and education. In addition, because mobile phones in Kerala are a private sector initiative rather than a development project, other than through perhaps raising interest rates for capital, they do not crowd out investments in other projects. Also unlike most development projects, the service is self-sustaining; mobile phone companies provide service because it is profitable to do so, and fishermen are willing to pay for mobile phones because of the increased profits they receive. This point is also relevant for reconciling our results with anecdotal evidence that government or NGO projects setting up internet kiosks or other information services for farmers in other developing countries often do not meet similar success. The welfare gains to be had are directly tied to, and in fact are indicated by, the profitability of both arbitrage and mobile phone provision, and the private sector may be better suited to identifying such opportunities.

In generalizing the results, it should be noted that the perishability of fish is an important reason why there was so much waste and inefficiency before mobile phones and why better information has such a large impact on market performance and welfare. While there is evidence that even markets in nonperishable commodities, such as grains, are often not well integrated spatially, the biggest gains will likely be for other perishable commodities, such as milk, eggs, fruits, and vegetables, and possibly even day labor, where spot labor markets often only clear locally (within villages). And there may be other factors relevant for market performance that interact with the availability of information, such as transportation infrastructure. For example, more recently in Kerala, improvements in roads have lowered the cost of land transport, leading to more arbitrage by wholesalers on land (and less by fishermen) since transport is now in many cases cheaper by road than by sea. In other cases, poor quality roads may limit the ability of improvements in information to enhance market performance because arbitrage remains prohibitively expensive. However, the widespread, voluntary adoption of ICTs for marketing by producers and traders observed in many developing countries suggests similar gains are likely to be found elsewhere.

Finally, in many countries, including India, there is a concern over a perceived internal digital divide, with both ICT access and the resulting benefits available only to the wealthiest or most educated, leaving all others behind. However, the evidence here suggests that the benefits of ICTs can be found among fishermen or farmers, not just software engineers or call-center workers. Further, while it was primarily the largest fishermen who adopted mobile phones in the present case, there were significant spillover gains for the smaller fishermen who did not use phones, due to the improved functioning of markets. Thus, rather than simply excluding the poor or less educated, the "digital provide" appears to be shared more widely throughout society.

Appendix: Proof of the Theorems

Proof of Theorem 1. Suppose there exists an equilibrium and that p^* represents the equilibrium price difference between the two markets when one catchment zone is in state H and the other is in state L. Let $\pi(x)$ represent the updated probability that a zone is in state H for a fisherman with catch x. By switching markets, the fisherman gains xp^* with probability $\pi(x)/2$ (the probability that their zone is in state H and the other is in state L) and loses xp^* with probability $(1 - \pi(x))/2$ (the probability their zone is L and the other zone is H); with probability ½, the two zones are in the same state, and they receive the same price as if they did not switch.[41] The equilibrium condition for switching is thus $(\pi(x) - 1/2)xp^* > \tau$. $\pi(x)$ is increasing in x since $f(x_i|d_i)$ satisfies the Monotone Likelihood Ratio Property, so the left-hand side of the previous equation is increasing in x, meaning that only fishermen with the highest values of x switch markets. Any equilibrium must therefore be based on a cutoff value of x, where all fishermen with catch greater than this value switch to the other market and all those below sell locally.[42] It is then straightforward to construct the equilibrium by walking down the distribution of catch from $x_{\max}$ to zero to identify the cutoff value, $x(\tau)$. If $\tau > (\pi(x_{\max}) - 1/2)x_{\max}p^*$, transportation costs are too high (given the uncertainty over the state of both zones), and no one switches in equilibrium. For smaller values of τ, some fishermen will switch to the other market. Let $p^*(x)$ represent the level of price dispersion between the markets when the two zones are in opposite states and fishermen with catch x or above switch markets. $p^*(x)$ is weakly increasing in the cutoff value x since fewer fishermen are switching as x increases. The equilibrium cutoff x^* for switching is defined implicitly by the equation $(\pi(x^*) - 1/2)x^*p^*(x^*) = \tau$. Each term on the left-hand side is increasing in x, so x is an increasing function of τ whenever there is an interior solution to this equation $(0 < x^* < x_{\max})$. So long as τ is positive, this equation cannot be satisfied near $x = 0$; it will never be worthwhile for a fisherman with a very small catch to switch markets. Thus, for $\tau < (\pi(x_{\max}) - 1/2)x_{\max}(P(Q_L) - P(Q_H))$, there must be an interior solution x^* to the equation above. And since $p^*(x)$ is increasing in x and the equilibrium cutoff x is increasing in τ, price dispersion as an implicit function of τ, $p^*(\tau)$, must also be increasing in τ. Finally, consider again the equilibrium condition for switching, $(\pi(x^*) - 1/2)x^*p^*(x) = \tau$. The first term on the left-hand side, $(\pi(x^*) - 1/2)$, the

41. The equilibrium must be symmetric. So when both zones are in the same state, an equal amount of fish flows from each zone to the other, leaving quantities and price equal in the two markets.

42. The equilibrium cannot involve a "gap" in who switches (i.e., a fisherman with $x < x(\tau)$), since if it is worth it for that fisherman to switch, it would also be worth it for all fishermen with catch above them to switch as well.

assessed likelihood that your zone is in an H-state and the other is in an L-state, reflects uncertainty regarding the state of both one's own zone and the other zone. Because this term will always be less than 1 (even if the state of one's own zone were known with certainty, nothing is known about the other zone), equilibrium price dispersion $p^*(x)$ will always exceed τ/x^*, the per-unit transportation costs for the marginal switcher. QED

Proof of Theorem 2. The proof follows that for Theorem 1 closely. Assuming that $\tau > \tau^*$ allows us to focus on the case where there is no switching in equilibrium if there is no search technology. We first show that fishermen with the largest catches gain the most from purchasing the search technology. By purchasing the search technology, the fisherman gains $xp^* - \tau$ in revenue with probability $\pi(x)/2$ (the probability that their zone is in state H and the other is in state L). So the equilibrium condition for purchasing the technology is $(\pi(x)/2)(xp^* - \tau) > \psi$. Since $\pi(x)$ is increasing in x, the left-hand side of the previous equation is increasing in x, meaning that only fishermen with the highest values of x purchase the search technology, and any price discovery equilibrium must be based on a cutoff value of x. We again construct the equilibrium by walking down the distribution of catch from $x_{\max}$ to zero to identify the cutoff value, now $x(\psi)$, where all fishermen with catch greater than the threshold buy the search technology and all those below do not. If $\psi > (\pi(x_{\max})/2)(x_{\max}(P(Q_L) - P(Q_H)) - \tau)$, information is too costly and no one purchases the search technology in equilibrium, which reproduces the no-arbitrage case. For smaller values of Ψ, some fishermen will purchase it. The equilibrium cutoff x^* for purchasing the search technology is defined implicitly by $(\pi(x^*)/2)(xp^*(x) - \tau) = \psi$. As earlier, each term on the left-hand side is increasing in x so x is an increasing function of Ψ whenever there is an interior solution to this equation ($0 < x^* < x_{\max}$). As stated, if $\psi > (\pi(x_{\max})/2) \times (x_{\max}(P(Q_L) - P(Q_H)) - \tau)$, there is no interior solution. So long as τ is positive, this equation cannot be satisfied near $x = 0$; it will never be worthwhile for a fisherman with a very small catch to switch markets, so they will never pay to acquire price information. Thus, for $\psi < (\pi(x_{\max})/2)(x_{\max}$-$(P(Q_L) - P(Q_H)) - \tau)$, there must be an interior solution x^* to the equation above. And since $p^*(x)$ is increasing in x and the equilibrium cutoff x is increasing in Ψ, price dispersion as an implicit function of the cost of search, $p^*(\psi)$, must also be increasing in Ψ (and, thus, reductions in Ψ weakly reduce $p^*(x)$). Finally, note also that from the equilibrium condition for

TABLE X
EFFECTS OF MOBILE PHONE SERVICE ON OUTCOMES AND WELFARE: SEPARATE TREATMENTS

	(1) Max–min spread	(2) Coefficient of variation	(3) Percent have waste	(4) Quantity sold	(5) Price	(6) Price (>0)	(7) Revenue	(8) Costs	(9) Profits
Region I	−.64	−.01	.005	35	.03	.13	352	−15	367
	(0.60)	(0.07)	(0.005)	(6.8)	(0.07)	(0.06)	(54)	(9.6)	(49)
Region II	−.05	−.07	−.02	32	−.01	−.18	182	.53	182
	(0.60)	(0.07)	(0.005)	(6.9)	(0.07)	(0.06)	(55)	(9.7)	(50)
Period 1	−.98	−.12	−.016	−3.1	.39	.33	85	2.5	83
	(0.48)	(0.05)	(0.004)	(5.6)	(0.06)	(0.05)	(45)	(7.9)	(41)
Period 2	−.64	.16	−.021	−14	.54	.44	30	−.91	30
	(0.46)	(0.05)	(0.004)	(5.4)	(0.05)	(0.05)	(43)	(7.5)	(39)
Period 3	−5.7	−.55	−.076	18	.85	.29	385	66	319
	(0.51)	(0.06)	(0.004)	(5.9)	(0.06)	(0.05)	(47)	(8.3)	(43)
RegionI_period1	−4.8	−.42	−.060	25	.16	−.41	199	93	106
	(0.68)	(0.07)	(0.005)	(7.7)	(0.08)	(0.07)	(62)	(11)	(56)
RegionI_period2	−5.6	−.44	−.062	24	.20	−.38	225	81	144
	(0.66)	(0.07)	(0.006)	(7.5)	(0.07)	(0.07)	(60)	(10)	(54)
RegionI_period3	−.73	−.07	−.006	−.36	.07	.15	56	41	15
	(0.72)	(0.08)	(0.006)	(8.1)	(0.08)	(0.07)	(65)	(11)	(59)
RegionII_period1	.09	.05	.004	−9.0	.04	.05	−52	−6.9	−45
	(0.68)	(0.07)	(0.005)	(7.8)	(0.08)	(0.07)	(62)	(11)	(57)
RegionII_period2	−5.7	−.34	−.036	12	−.01	−.32	197	73	123
	(0.66)	(0.07)	(0.005)	(7.6)	(0.07)	(0.06)	(60)	(10)	(55)
RegionII_period3	−.97	−.01	.018	−9.2	.04	.18	47	22	25
	(0.72)	(0.08)	(0.006)	(8.2)	(0.09)	(0.07)	(65)	(12)	(60)
Observations	747	747	74,700	74,700	74,700	73,335	72,764	74,700	74,700

Data from the Kerala Fisherman Survey conducted by the author. Standard errors, clustered at the village level, in parentheses. All prices in 2001 Rs.

purchasing the phone, we can see that as Ψ goes to zero, the cutoff for purchase is driven to the x that would switch if both zones were known with certainty and the zones were in opposite states, and equilibrium price dispersion p^* goes to τ/x. QED

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