The Food Corporation of India and the Public Distribution System: Impacts on Market Integration in Wheat, Rice, Pearl Millet, and Corn

by
Mindy L. Mallory and Kathy Baylis

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Mindy Mallory

and

Kathy Baylis[1]

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[1] Mindy Mallory (mallorym@illinois.edu) and Kathy Baylis are Assistant Professors in the Department of Agricultural and Consumer Economics at the University of Illinois. Funding support from the ADM Institute for the Prevention of Postharvest Loss is gratefully acknowledged.

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Abstract

This paper examines the spatial integration of major staple commodity markets in India. We consider wheat, rice, pearl millet, and corn markets. This set represents the two most highly regulated crops, wheat and rice; and two that are regulated to a lesser degree, pearl millet and corn. Our data come from the states of Bihar, Haryana, Uttar Pradesh, and West Bengal, states that produce a large share of India's cereal grains. Access to food remains an important issue for India as it develops. Because of this, the Indian government regulates the markets for staple foods heavily, requiring almost all grain be marketed through government licensed mandis. The government enforces a minimum price in the regulated markets by placing government buyers in each market that will purchase any amount of grain meeting minimum quality standards at the minimum support price. This activity results in the government being the primary entity engaged in the storage of staple food crops. These market interventions discourage private investment in storage capacity among farmers and traders who handle grain in the private sector, which could impact market integration and efficient price transmission. However, we find the strongest evidence for market integration in the rice markets, which is one of the most regulated of the crops considered. Therefore, there seems to be some benefit from the government's market making activities that may compensate for a lack of infrastructure to facilitate market integration.

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Introduction

In this paper we examine the spatial integration of staple food commodity markets in India. Food-grain crops are highly regulated in India, with floor prices for farmers, government purchases and subsidized sales to consumers. State-specific regulations on storage and transport further limit internal grain movement. In 2002 and 2003, India reformed its domestic grains policies, with a particular eye to removing barriers to inter-state trade. In this paper we ask whether Indian grain markets are integrated after the imposition of these reforms.

While India has enjoyed rapid growth for the past twenty years, it still struggles with development challenges, particularly around access to food. India hosts the world's second largest population, and although incomes have been rising, it faces large income inequalities and one of the highest rates of child stunting in the world. Since India's independence in 1947, the government established a large social assistance program to support the incomes of rural farmers while providing affordable food for its urban poor. These goals are executed primarily through two programs: The Food Corporation of India (FCI) procures staple food crops from farmers, often at higher than market prices. Then the Public Distribution System (PDS) sells to the poor through government-run Fair Price Shops. This intervention comprises a large share of the market for staple crops. For example, the FCI purchases nearly twenty percent of the total wheat crop in India, and in the state of Punjab, the FCI purchases nearly eighty percent of the crop (NMCE 2009). As Indians move from the countryside and subsistence agriculture to urban areas and non-agricultural jobs, the performance of the agri-marketing system is more important than ever.

The government promises to purchase any grain that meets the standard of Fair Average Quality at a stated Minimum Support Price (MSP), thus creating an effective floor on the price of the grain. However, since they actually physically purchase the grain at a price fixed throughout the year, the government stores much of the grain and the private sector has no incentive to invest in storage. Furthermore, the FCI does not maintain adequate storage facilities to prevent losses during storage from moisture and pests. Roughly twenty percent of cereal grains and oilseeds are lost post-harvest due to a lack of adequate storage facilities (OECD 2007).

In 2002 and 2003, India reformed the Stock Limits and Movement Restrictions on Specified Foodstuffs. These policies were intended to limit the state-level restrictions on grain storage and movement and create a more unified domestic market. At the same time, the licensing requirement for dealers was also removed. Any dealer could now buy, sell, store or transport any quantity of wheat, paddy/rice, coarse grains, pulses, wheat products, and some other commodities without a license. Some state-specific restrictions persist, however, and when combined with substantial federal market interventions and poor marketing infrastructure, one might anticipate that price transmission among markets may continue to be limited.

In this paper we examine the spatial integration of wheat, rice, pearl millet and corn markets across the northern grain belt, specifically considering the states of Bihar, Haryana, Uttar

Pradesh and West Bengal India. Rice and wheat are the primary staple crops and while pearl millet and maize still face MSPs, they face fewer state storage and transport restrictions since they are perceived as being less crucial for food security.

Prices are obtained from AgMarkNet[2], the data portal of the Indian Ministry of Agriculture. We use monthly local prices from 2001 to 2010 in the five most active markets in each state we consider. We estimate a spatial cointegration model as proposed in Ardeni (1989), Goodwin and Schroeder (1991), and Ardeni (1991) to determine the level of integration among these markets.

We see three primary contributions of this study. First, to our knowledge, this is the first paper to test whether Indian grains markets are spatially integrated after the 2002/2003 reforms. In this test, we use detailed spatial data of prices at multiple local markets in the producing regions of India. Second, we use a relatively novel approach to address the large fraction of missing observations in the data. We find little evidence that markets are spatially integrated, and see substantial differences by states and crops. Haryana has the most spatially integrated markets for rice and wheat, but not for pearl millet. Thus, even when controlling for similar infrastructure within the same state, we do not see integration of the smaller but less regulated crop. The crop with the most integrated markets is rice, which is interesting since rice is clearly the most highly regulated crop, particularly during this time period where we also saw the imposition of an export ban. Our findings raise the question as to whether the limited degree of integration we observe is in fact an artifact of homogenous government policy instead of being indicative of active arbitrage.

Background

The Indian government is highly involved in Indian agriculture. The Essential Commodities Act (ECA) was established in 1955 and regulates commodity prices through government purchases, licenses and permits which limit the movement, distribution and disposal of commodities deemed essential such as cereals, pulses, edible oilseeds, oilcakes, raw cotton, sugar, and jute (OECD 2007). Similarly, the Agricultural Produce Market Regulation Act (APMRA) requires that farm produce be sold only at regulated markets through registered intermediaries. Until recently, food-processing industries were limited by regulation to small-scale capacities and small-scale, low technology firms still dominate the industry (Government of Canada 2008)

In 1965, the Indian government established the Food Corporation of India (FCI) to procure, store, and distribute food-grains at the national level, including handling and distributing all grain imports. That same year, the Agricultural Price Commission was established to set prices to balance producer and consumer interests (Ghosh 2010). State zones were also introduced and grain movement out of surplus states and districts was restricted. Part of the purpose of these restrictions was to lower local prices to facilitate government grain purchases which would then be sold to the poor through the public distribution system (PDS) in consuming regions. The specific procurement method varied by state (Radhakrishna and Indrakant,1988). Along with being costly, the World Bank (1999) found that these programs discouraged private trading in food grains and undermined investment in India's long- term food security.

[2] AgMarkNet is the website of the Indian Ministry of Agriculture http://agmarknet.nic.in/

Recent Reforms

Reforms in the domestic market occurred mainly during the 1990s and early 2000 period after trade liberalization. In the early 2000s, the ECA was amended to remove the licensing requirement of dealers and restrictions on the storage and movement of food grains, sugar, oilseeds and edible oils. Specifically, in 2002, the Removal of Licensing Requirements, Stock Limits and Movement Restrictions on Specified Foodstuffs Order was passed and amended in 2003 to allow any dealer to freely buy, sell, hold or trade any quantity of food-grains and oilseeds without a license. The reform measures also abolished selective credit controls used to regulate institutional credit to traders. These changes also require state governments to get the prior approval from the center before passing new orders (Jha, Srinivasan, and Ganesh Kumar 2010). Similarly, the sugar control order and the milk and milk products order have also been amended to encourage greater participation by the private sector in the marketing of these commodities (OECD 2007).

As a result of these reforms, state traders no longer have a monopoly on trade. After 2003, the private sector was allowed to establish parallel markets for the agricultural commodities under the Model Market Act (Jayasuria, Kim and Kumar 2007), and agricultural futures markets are now operating in several commodities.

Continued constraints to grain market integration

Despite these reforms, substantial government intervention persists. Commodity specific institutions regulate markets through an array of measures including minimum support prices, import subsidies, public procurement and distribution of food grains. The Agricultural Produce Marketing Committee (APMC) in the states also restricts the growth of agricultural marketing and does not allow co-operatives and private parties to set up modern markets at will. Government institutions also control and distribute inputs, develop infrastructure, and provide general services (OECD 2007). Although the changes have reduced the barriers to internal trade to a large extent, certain other restrictions continue to limit interstate trade. For example, traders are required to own national and interstate permits, pay state-specific taxes for the sale of certain goods, and suffer additional transactions costs (poor roads, extensive paperwork, multiple checking, and clearance requirements) (Jha, Srinivasan, and Ganesh Kumar 2010).

The lack of infrastructure, including roads, power and storage can reduce agricultural investment, price transmission and increase post-harvest losses. The OECD (2007) estimated post harvest losses for grains, fruits and vegetables to be 25% to 30%. But private investment in storage is discouraged by fixed annual MSPs and the presence of large government stocks. In 2011, government stocks were estimated to be more than double the prescribed limit, which constrains price movement and spatial integration (47.1 million tonnes versus 20 million tonnes as of January 1st, 2011) (Gulati 2011)

Previous Literature

Previous work on the spatial integration of Indian feed-grain markets is mixed. Palaskas and Harriss-White (1993) used the Engle and Granger (1987) method of cointegration to test weekly prices of rice, potato and mustard collected from three markets places in Burdwan district of West Bengal (India), and found cointegration for most pairs. One concern about their approach is that results from the Engle and Granger (1987) method of cointegration are very sensitive to the choice of a variable for normalization (Ghosh 2010). Their study was also limited by its use of a very short span of data (weekly data for a period of less than three years).

Jha et al (1997) study market integration using monthly data for 44 rice markets and 47 wheat markets for January 1980 to December 1990, again using the Engle-Granger methodology. They observed that all pairs were integrated of order one, implying that prices of rice as well as of wheat are cointegrated. Based on these results, they concluded that food markets all over India are highly integrated (Ghosh 2003). In a later paper, however, the same authors find that there is a tendency to hoard rice stocks, with the wholesalers holding more than optimal inventories (Jha and Nagarajan 1998). They also find evidence of substantial information asymmetries in the grain markups (Jha et al 1999). They suggest that government intervention and the presence of a parallel controlled market create substantial information asymmetries.

Later work by Jhar, Murthy and Sharma (2005) use the methodology from Gonzalez-Rivera and Helfand (2001) and find that Indian grain markets are not integrated. Specifically, the authors look at monthly prices from 55 rice markets from 1970 to 1999 and find significant regional fractionalization.

Ghosh (2003, 2010) uses the maximum likelihood methodology to test for cointegration (Johansen 1988), indicating whether grain markets are cointegrated within and across the major producing states. He finds that for Uttar Pradesh all the prices are pair-wise cointegrated, which indicates that the weak version of the law of one price holds in these markets. The cointegration results for the remaining three states, Haryana, Rajastan and the Punjab indicate that the prices are not pair-wise cointegrated. For rice, again, the evidence is mixed. For Orissa, he finds that regional market are integrated. However, no evidence is found for the law of one price holding in rice markets in the states of Bihar, Uttar Pradesh and West Bengal. The results for inter-state spatial integration of rice markets represented by four market centers chosen from the four selected states reveal that even though the markets were integrated, the law of one price was not in operation in Haryana, Punjab, and Rajasthan. As Ghosh states, “The cointegration results for Bihar and UP indicate that the regional wheat markets were integrated to such an extent that the weak version of the LOP was in operation. The cointegration tests also offer evidence for spatial integration of regional wheat markets in Haryana, Punjab and Rajasthan; but no evidence is found in favour of the weak version of the LOP for these states. The results for inter-state regional wheat markets represented by four market centers chosen from the four selected states reveal two cointegrating vectors and two common stochastic trends. Thus, even though all the I(1) prices taken together are linked in a long-run relationship for both rice and wheat, they are not pair-wise cointegrated in most cases. These results suggest that regional rice and wheat markets within and across the states are spatially linked in the long run.” Ghosh concludes that food-grain markets are largely integrated, and therefore government can let the private market have a larger role.

In terms of the connection of domestic to international grain markets, again, the evidence is mixed. Shekhar 2004 regresses domestic price on domestic production and international price, and finds evidence of some international price transmission to domestic markets, but not the large domestic producing areas. Jayasuria, Kim and Kumar (2007) use panel unit root tests and find that after the reforms in 1994, rice prices in India converge much more quickly to the international price. Naik and Jain 2002 estimate the efficiency of future's markets in India, and find that the markets are still in their infancy, and are not yet efficient.

In this study, the methodology that we employ is similar to many of the studies described above. Specifically, we use a vector error correction model and Johansen tests for cointegration to test for the presence of a long run equilibrium in Indian wheat, rice, pearl millet, and corn markets. However, we employ a novel method to deal with missing data, and use a different approach to group markets for analysis compared to the studies described above. The studies described above did not discuss their strategies for dealing with missing data. One must infer that the authors of these studies employed list-wise deletion for dates where missing data were present. Since we analyze a large number of markets at once in this study, list-wise deletion would require us to throw away much valuable information because list-wise deletion requires deleting the entire row of data if information for even one market is missing. In order to retain the full information available in the dataset we employ the method of multiple imputation to deal with missing values.

Further, many of the studies above (aside from Gosh) tested for cointegration in pairs of markets, as a way of dealing with the dimensionality of the problem. This method also minimized the information lost by performing list-wise deletion. However, markets that are integrated may exhibit more complicated dynamics and long run relationships than can be captured by the pairwise model. For example, after testing for cointegration between two pairs of markets it is possible to conclude that each pair is not cointegrated, but in fact, the four tested all together are cointegrated.

Data

Each regulated mandi must report the minimum, maximum, and modal prices to the Ministry of Agriculture on each day and for each crop that a transaction occurred. The Ministry of Agriculture makes these data available to the public, and we obtained data on wheat, rice, pearl millet, and corn prices from the Indian Ministry of Agriculture's website, agmarknet.nic.in. Our data set contains daily prices from 2005 through 2011. The nature of the reporting requirement results in a significant number of missing observations in the raw dataset. For example, if a mandi transacted wheat on only one day from 2005 to 2011, this market would show up in our dataset, but every row except one would be missing. From the number of missing observations, we observe that many mandis in our data set are not major markets in the commodity of interest and contribute to the large number of missing daily price data we observe in our data.

Since we are interested in measuring spatial market integration we filter out mandis that are not major points of transaction in the following way. First, we calculate a monthly median price to create a monthly time series for each mandi. Then we remove mandis for which more than 50% of the data are missing. Since the median is a measure of central tendency, we may be introducing a degree of correlation among the variables, but given the sparse data, we felt that we should avoid the strong influence of outliers which would result from using the mean monthly price. Alternatively, we could have used a point-based rule to create the monthly series. For example, we could have chosen the price on the first Friday of every month. We used the monthly median for two reasons. First, since we are examining the nature of spatial market integration, we would rather err in the direction that makes us more likely to conclude the markets are integrated. That way, if we conclude that the markets are not integrated, it is less likely due to the way in which we constructed our dataset. Second, if data are sparse and we used a point-based rule, we would need to construct the series according to an algorithm that choose the first Thursday if the first Friday was missing, the first Wednesday if the first Friday and first Thursday were missing, etc. Markets which have sparse data will be more likely to produce observations for the month that are many days apart from the target date. Using the median monthly price minimizes this effect.

Figure 1 shows the locations of the mandis retained, by commodity, according to the filtering rule described above.[1] Table 1 provides a detailed breakdown of how many mandis are in our dataset by state and by commodity. We retained the most number of mandis in the states of Haryana, Uttar Pradesh and West Bengal (for rice). As we interpret our results on market integration, we will focus on these states because they are the least likely to be plagued by issues of sparse data.

The fact that we are only able to retain such a small number of markets using this filtering rule already hints at the nature of market integration and the incentive to store in the countryside. The vast majority of markets dropped are locations that have active transactions only during the busy harvest season. At other times of year, we only observe a few markets that are buying and selling grain actively. It is this much smaller sample of markets that we retain for our analysis. With such a small number of markets transacting in the off-season, it is clear that many farmers do not have easy access to nearby markets during these times. Thus, many farmers must sell grain during the harvest season, or rely on traders to come through the village if they want to store and sell in the off season. This creates an incentive to sell the majority of one’s marketable crop at harvest, when access to nearby markets is greatest. This incentive to sell at harvest-time also is reinforced by credit practices that are common to rural Indian agriculture. Often farmers take out small operating loans to pay for seed or other supplies needed to plant their crops. At harvest these loans comes due, creating an extra need for cash at harvest-time Kumar, Turvey, and Kropp (2012). The incentive to sell when one has access to a nearby market, and the incentive to obtain cash to pay one’s debtors at harvest work together to create a powerful incentive to sell most of one’s grain at harvest rather than storing any marketable surplus for later sale.

Multiple Imputation

Even after culling multiple sparse markets, we are left with a considerable amount of missing data in our retained set of mandis. The most common method for dealing with missing data in time-series applications is to simply delete the missing data and analyze the remaining data. In our case, this is an unreasonable solution. Our dataset contains a fairly wide panel of mandis observed over time. If we employ list-wise deletion, if a data point is missing from just one mandi we would have to delete the entire row and discard much valuable data.

The second most common method for dealing with missing data is to perform a simple imputation of the data. In a time-series setting this is often accomplished by linearly interpolating the observation using the two nearest observations (Friedman 1962). However, simply imputing using the mean of the conditional distribution of the data can greatly reduce the variance of the resulting sample and thereby affect inference (King et al. 2001).

We employ the method of multiple imputation, which generates *m* completed datasets making random draws from the conditional distribution over the missing data. The method of multiple imputation was recently extended to the context of time-series cross-section data (as is our dataset), which specifically allows for smooth time trends and correlations across time and space to be considered in the imputation model (Honaker and King 2010).

The *m* completed datasets are the same for the observed data points, but the missing data are replaced by draws from the posterior density and hence incorporate the relevant level of uncertainty associated with those data points. Below we test for spatial market integration on each of the *m* imputed datasets, and combine the results in such a way that accounts for the uncertainty in the coefficient estimates both within and across imputed datasets (Rubin 1976). We describe in detail below how the results from the *m* completed datasets are combined.

To perform the multiple imputation algorithm, we employ the Amelia package available for the R statistical software (Honaker, King, and Blackwell 2011).[2] Figure 2 illustrates the imputed datasets for selected markets. Rather than providing graphs of price series for all 95 price series, we demonstrate the range of missing observations we face in this analysis by featuring markets representing the states and commodities that we cover. Black dots correspond to observed prices, while the red dots represent the mean of the imputed data points and the red vertical bars represent the 95% confidence interval over the imputed data.

Properties of the Data

We use the Augmented Dickey Fuller (ADF) test to determine the order of integration of each (imputed) time series (Enders 2009). When we test for spatial market integration below, we will focus on the mandis at which a particular commodity is sold, by state. That is, we will group markets as indicated in table 1 when we perform the test for spatial integration. To enable that arrangement, each series in the group must be integrated of the same order, while the ADF test is conducted on each series individually and potentially may indicate a different degree of integration for each separate time series. In table 2 we summarize the results of the stationarity tests that we use to inform our modeling decisions in the next section. Most of our data was in fact non-stationary and integrated of order one. In the groups of mandis for which we concluded the data were integrated of order one, we failed to reject the null hypothesis of a unit root in almost all markets. There were a few cases however, where there was one or two mandis in which the null hypothesis of a unit root was rejected. In these cases we removed the mandi whose prices are stationary so that we can employ models designed for non-stationary data. In a few cases, specifically rice markets in Bihar and Haryana and Corn markets in West Bengal, the data were overwhelmingly stationary. An appendix contains the full ADF results for each market.

Testing for Spatial Market Integration

Following Ardeni (1989), Baffes (1991), and Goodwin and Schroeder (1991), we test for spatial market integration using a reduced form vector autoregression (VAR) in levels on the stationary markets, and we test for cointegration and the presence of a long run equilibrium in the groups of non-stationary markets using a vector error correction model (VECM) (Enders 2009).

The vector error correction model is specified in equation (1).

$$(1) \quad \Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \, \Delta X_{t-i} + e_t$$

First differences of the *n* price series are stacked in ΔX_t, β' is an $r \times n$ matrix that contain the *r* long-run equilibrium relationships, α is an $n \times r$ matrix containing speed of mean reversion parameters, *k* is the lag length of the model, ΔX_{t-i} are time lags of the first differences in prices, Γ_i are matrices of coefficients, and e_t is the normally and identically distributed error term. We are most interested in testing the significance of the alpha parameters in the VECM model, because these parameters indicate the mandis where the commodity price adjusts to deviations in equilibrium. Observing this adjustment can be evidence that there is some measure of arbitrage activity between markets so that if the price is higher than transport plus transaction costs traders or others will step in and arbitrage the price differential within the bounds of transport and transaction costs. Additionally, the coefficient estimates in the Γ_i matrices are commonly referred to as short-run effects, and significance of these coefficients can indicate how a shock that is localized to one market is diffused through the system to other markets.

In a well-functioning marketplace, this process is the mechanism that incents grain to move from surplus (producing) regions to deficit (consuming) regions. If we do not observe this type of price relationship, it may be a sign that insufficient incentives exist for grain to flow from where it is stored to where it is consumed.

For the groups whose market prices are stationary, we fit a VAR model as in equation 2.

$$(2) \quad X_t = \Gamma_0 + \sum_{i=1}^{k-1} \Gamma_i \, X_{t-i} + e_t$$

Levels of the price data are contained in X_t, Γ_0 is an $n \times 1$ vector of constants, Γ_i are matrices of coefficients, X_{t-i} are time lags of the price levels, *k* is the lag length, and e_t is a normally and identically distributed error term. We perform Granger causality tests on the coefficients in Γ_i, in this way we can determine which markets respond to price shocks in other markets. Similar to the intuition in the non-stationary model, we infer that markets that are well integrated if they are responses to shocks in other markets. If it were not so, price shocks in one market could potentially generate persistent opportunities for spatial arbitrage.

We determined the lag lengths, *k*, based on the Akaike Information Criterion for each group of markets which were modeled as a system. The number of equilibrium relationships, *r*, in the

VECMs we determined by the Johansen trace tests (Enders 2009). We used the vars package in R to perform the estimation (Pfaff 2008).

Results

We fitted VECM or VAR for each group of markets defined in Tables 1 and 2. Markets whose prices are stationary were fitted to a VAR and the groups of markets whose prices were non-stationary were fitted to a VECM because the Johansen trace test indicated that cointegration was present in each of these groups. Our approach to examining the markets in this study is somewhat unorthodox. Typically, one would focus on a few markets of interest, estimate one of the models described above on these markets, and one would spend a considerable amount of time interpreting each individual coefficient. Here, the scope of our inquiry is broader, and we cover many mandis within each group of interest. This prevents us from discussing the entire scope of our results in detail, but rather, we present a summary of the results that gives a more holistic description of the state of market integration in India than we could achieve by picking out a few select markets and analyzing whether or not these are integrated.[3]

Diagnostics of Multiple Imputation Results

It is instructive to discuss at least a portion of the results from one of the groups in detail to illustrate the way in which we incorporate the variation introduced by using the method of multiple imputation. Table 4 contains the estimated results from the Ellanabad equation in the Haryana wheat VECM. The names of the right hand side variables are presented in the first column. The Johansen trace test for cointegration indicated that there were three equilibrium relationships present in this market. The first three rows are named ect1, ect2, and ect3, which represent the error correction terms in this equation. The second column, titled 'Combined', contains the coefficient estimates and their standard errors for the right hand side variables. The results in this column combine the results across the *m* completed datasets into one coefficient estimate and one standard deviation for each. Specifically, if $\hat{Q}_i$ represents one estimated coefficients from imputed dataset *i* from equation (1) or (2), then the coefficient estimate combined across the *m* imputed datasets is simply the average of the coefficient estimates, $\bar{Q} = \sum_{i=1}^{m} \hat{Q}_i$. Calculating the combined standard errors is a bit more complicated because one needs to include both the within imputation and across imputation variation in this measure. The inclusion of the imputation uncertainty is, in fact, the advantage of the multiple imputation method in that it allows one to incorporate a reasonable amount of uncertainty due to the missing data. If one ignored the uncertainty associated with the missing values, one would over-reject the null hypothesis that the coefficient is zero. To this end, the total variance of the coefficient estimate is given by

$$T = \bar{U} + \left(1 + \frac{1}{m}\right) B ,$$

where $\bar{U}$ is the average within imputation variance, or $\bar{U} = \sum_{i=1}^{m} \hat{U}_i$, and B is the between imputation variance, or $B = \frac{1}{m-1} \sum_{i=i}^{m} \left(\hat{Q}_i - \bar{Q} \right)^2$. More on the method of combining results across multiple imputed datasets is found in Rubin (1976) and (1987). The parameter estimates presented in the column titled 'Combined' can be interpreted in the usual way.

The third column displays the *p*-values associated with the *t*-statistics obtained from dividing the parameter estimate by the standard error in column 2. In this case, ect1 is significant in the Ellanabad equation meaning that the price of wheat at Ellanabad responds to a group shock to bring the prices back into equilibrium defined by ect1. The only short run effect that is significant in this equation is that lagged changes in the price of wheat at Tarori.

In the fourth and fifth columns of table 5 we present the results without accounting for the across-imputation variation. That is, the fourth and fifth columns calculate the point estimates of the parameters in the same way, namely $\bar{Q} = \sum_{i=1}^{m} \hat{Q}_i$, but the variance of the parameter estimate is obtained by $T = \bar{U}$. The results obtained by this method of combining the results across the multiple imputed datasets puts a lower bound on the standard deviation of the coefficient estimates and is quantitatively the same as if we performed a single imputation that replaced the missing data with its conditional mean.

We felt it was important to put bounds on the estimates because one might be concerned that our results were affected too much by the missing data, and that if we do not find much evidence of market integration in the groups of markets considered, it may be due to the fact that we inflated the standard deviations of the coefficients too much when we accounted for the between imputation uncertainty, *B*. Comparing the coefficient standard deviations in columns 2 with the coefficient standard deviations in column 4, one can see that the standard deviations are not inflated by a large degree. This result is also apparent by examining the *p*-values in columns 3 and 5. Only in the case of the constant term did the alternative methods of combining the standard deviations across the multiple imputed datasets result in a drastic reduction in the *p*-value.

In the sixth and seventh column we provide another diagnostic of the combination of the results across multiple imputed datasets. Here we performed tests of significance of α_i for each of the imputed datasets. Then we counted the number of instances in which the coefficient was significant, and report the proportion of such cases in columns six and seven. Roughly speaking, it appears that the combined results presented in columns two and three were significant at the 5-10% level if the proportion of imputed datasets in which the coefficient was significant was roughly greater than half.

Main Results

The main results for the non-stationary data are found in table 3. Here we present a concise summary of the market integration results by displaying the proportion of mandis in the group for which at least one of the error correction terms is significant in at least one of the equations (in the first column) and the proportion of mandis in the group for which at least one of the short run effects were significant in at least one of the equations. That is, column 1 indicates the proportion of equations in which α_i is significant in equation *i*, and column 2 indicates the proportion of equations in which one of the $\Gamma_{i,j}$ is significant in equation *i*.

For example, row one contains the summary for the group of mandis in the state of Haryana that sell wheat in our dataset. In the first column we report that in three out of eight total mandis at least one of the error correction terms was significant. We may conclude then, that three of the eight mandis are integrated with one another, while five of the mandis where wheat is traded in Haryana do not appear to adjust to maintain a long run equilibrium with the other mandis. One can see in the second column of row one that no short run effects were significant in any of the mandis trading wheat in Haryana.

Even with a relatively low level of spatial integration, it appears that rice markets in Haryana are the most integrated of the markets we consider. Three out of six respond to deviations from long-run equilibrium, and all six mandis respond to at least one of the short-run changes in one of the other markets.

Considering our last group in Haryana, pearl millet markets are the least integrated in this state. Although we observed the second largest number of mandis in this group, twelve, only two of these responded to deviations from a long-run equilibrium condition. Further, no mandis in this group responded to short-run price changes in other markets.

Looking now to the state of Uttar Pradesh, we observed thirteen mandis in rice in this state, but only two of them responded to deviations from a long-run equilibrium condition. However, six out of the thirteen mandis responded to short-run price changes, indicating that in this group, market integration may occur predominately through short run effects rather than long-run effects. Pearl millet markets in Uttar Pradesh appear to have a similar degree of integration (or lack thereof) as pearl millet markets in the neighboring state of Haryana. Here, two of the eight mandis responded to deviations from a long-run equilibrium condition, and none of the mandis responded to short-run price changes in the other markets.

Finally, we observe a group of ten mandis trading rice in West Bengal. These markets do not appear to be as well integrated as the rice markets in Haryana and Uttar Pradesh with only one out of ten responding to deviations from long-run equilibrium and two out of ten responding to short-run price changes in other mandis.

Discussion and Conclusions

In conclusion, we observe substantial fractionalization in grains markets in the producing states in India. We also observe substantial differences in the degree of integration among states and crops. A lack of observed spatial market integration can result from high and variable transportation costs from one market to another, from either lacking physical or market information infrastructure . Second, a lack of observed spatial market integration can also result from limited storage near one market which will limit the ability of farmers or traders to take advantage of post-harvest arbitrage opportunities. Third, government price and storage policies can also generate market fractionalization, particularly between producing and consuming regions. As one might anticipate, we see a higher degree of spatial integration in the wealthier states of Haryana and Uttar Pradesh, and less in West Bengal. Thus, state-level differences clearly matter.

In our results, we see those crops that are mostly highly regulated, wheat and particularly rice, to have the highest degree of spatial integration. Note that during this period, the federal government instituted export bans on both crops and changed MSPs several points during the year, so the price coordination may in part be a result of those national interventions.

This result is particularly notable in the case of the state of Haryana where physical infrastructure is relatively good and markets are more modern. Even here however, we see no evidence of market integration in pearl millet despite seeing some evidence in wheat and rice. Thus, controlling for infrastructure, we observe the smaller, less regulated market also being less integrated.

Much more work needs to be done. We would like to explicitly be able to test whether the limited market integration we observe in wheat and rice prices is driven by MSPs. Second, we would like to test the effect of considering a smaller sample of markets in each state affects our results, and how the degree of integration varies across space within a state. Given we also observe quantities traded, we could limit our study to only those markets handling a large volume to observe whether the lack of integration is only driven by thin markets.

In this paper, using comprehensive spatial integration techniques and appropriately dealing with missing observations, we observe a significant lack of spatial market integration in India. Thus, we argue that this finding raises the concern that farmers are not able to benefit from arbitrage opportunities and may not receive appropriate price signals. It is also clear that India's market reforms of the early 2000s were insufficient to develop a fully integrated, low-transaction cost grain market for her farmers.

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Table 1: Number of Markets observed by state and commodity

State	Wheat	Rice	Pearl Millet	Corn
Bihar	--	1	--	--
Haryana	8	6	12	2
Kerala	1	--	--	--
Uttar Pradesh	23	13	8	9
West Bengal	--	10	--	2

Table 2: Stationarity Summary[a]:

State	Wheat	Rice	Pearl Millet	Corn
Bihar	--		--	--
Haryana	X		X	X
Kerala	X	--	--	--
Uttar Pradesh	X	X	X	X
West Bengal	--	X	--	

[a]X indicates unit root,   is stationary, -- indicates no data

Table 3: VECM Summary[a]:

State, Commodity	Proportion of Equations in which at least one ect term is significant	Proportion of Equations in which at least one short run effect is significant
Wheat, Haryana	3/8	0/8
Rice, Haryana	3/6	6/6
Pearl Millet, Haryana	2/12	0/12
Rice, Uttar Pradesh	2/13	6/13
Pearl Millet, Uttar Pradesh	2/8	0/8
West Bengal	1/10	2/10

Table 4: Estimated results in the Ellanabad equation of the Haryana wheat VECM.

	Combined	p-values	Alt	p-values	Proportion Sig 0.05	Proportion Sig 0.10
ect1	-0.5	0.05	-0.5	0.02	0.66	0.76
	(0.28)		(0.21)			
ect2	0.09	0.41	0.09	0.39	0.06	0.16
	(0.39)		(0.32)			
ect3	-0.07	0.32	-0.07	0.3	0.12	0.24
	(0.15)		(0.14)			
constant	-177.64	0.5	-177.64	0.05	0.52	0.66
	(14191.57)		(95.55)			
ΔEllanabad$_{-1}$	-0.29	0.07	-0.29	0.04	0.54	0.62
	(0.18)		(0.15)			
ΔFatehabad$_{-1}$	-0.03	0.47	-0.03	0.46	0.06	0.12
	(0.32)		(0.26)			
ΔKaithal$_{-1}$	0.01	0.48	0.01	0.48	0.04	0.04
	(0.15)		(0.14)			
ΔRania$_{-1}$	0.44	0.11	0.44	0.06	0.44	0.56
	(0.34)		(0.27)			
ΔSirsa$_{-1}$	0.18	0.3	0.18	0.26	0.12	0.22
	(0.33)		(0.27)			
ΔTarori$_{-1}$	-0.49	0.03	-0.49	0.01	0.76	0.86
	(0.23)		(0.19)			

Wheat Markets

Rice Markets

Pearl Millet Markets

Maize Markets

Figure 1: Mandi Locations by Commodity

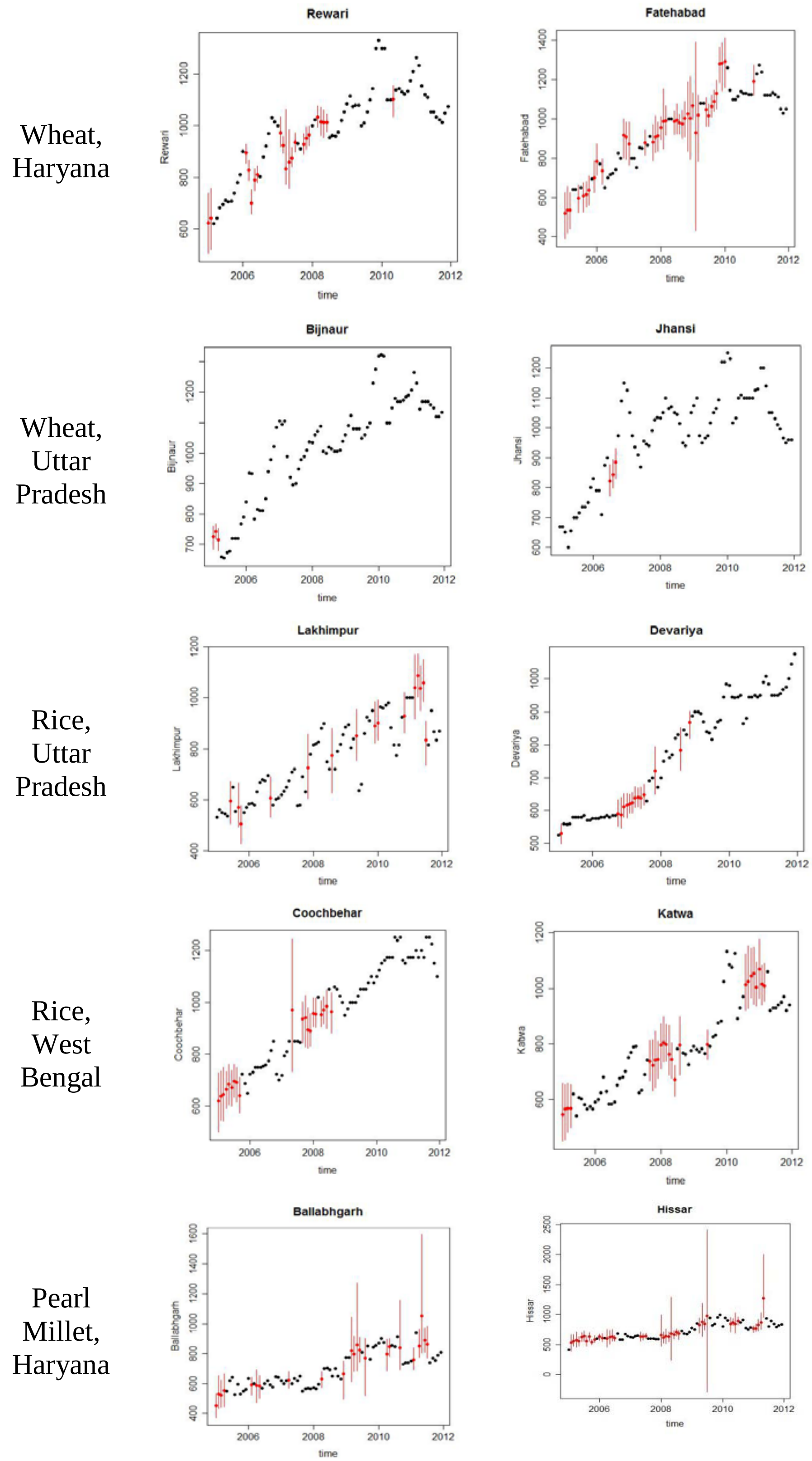

Figure 2: Imputed price series, selected markets

Appendix

A.1 Stationarity tests in Haryana wheat markets

	ADF Statistic	Lag Order	p-value
Ballabhgarh	-3.33	4	0.15
	0.73		
Ellanabad	-2.31	4	0.46
	0.53		
Fatehabad	-1.99	4	0.57
	0.54		
Palwal	-3.06	4	0.15
	0.18		
Panchkula	-1.96	4	0.59
	0.52		
Pataudi	-3.76	4	0.03
	0.31		
Rewari	-2.62	4	0.33
	0.27		
Sirsa	-2.70	4	0.30
	0.58		

A.2 Stationarity tests in Uttar Pradesh wheat markets

	ADF Statistic	Lag Order	p-value
Agra	-2.59	4	0.34
	0.05		
Azamgarh	-2.73	4	0.28
	0.04		
Bahraich	-3.02	4	0.16
	0.07		
Ballia	-3.07	4	0.14
	0.06		
Bareilly	-2.98	4	0.17
	0.00		
Bijnaur	-3.14	4	0.11
	0.02		
Devariya	-2.12	4	0.53
	0.02		
Faizabad	-2.97	4	0.18
	0.15		
Gazipur	-3.35	4	0.07
	0.00		
Ghaziabad	-3.06	4	0.16
	0.31		
Gorakhpur	-2.96	4	0.18
	0.03		
Hapur	-2.74	4	0.27

	0.08		
Jaunpur	-3.53	4	0.04
	0.08		
Jhansi	-1.87	4	0.63
	0.10		
Kosikalan	-2.37	4	0.43
	0.00		
Lakhimpur	-2.97	4	0.18
	0.03		
Lalitpur	-2.19	4	0.50
	0.01		
Mathura	-2.34	4	0.44
	0.00		
Muzzafarnagar	-3.09	4	0.13
	0.00		
Raibareilly	-2.49	4	0.38
	0.06		
Rampur	-2.82	4	0.24
	0.00		
Sitapur	-2.33	4	0.44
	0.14		
Unnao	-2.14	4	0.52
	0.00		

A.3 Stationarity test Kerala Wheat market

	ADF Statistic	Lag Order	p-value
Alleppey	-1.65	4	0.72
	0.24		

A.4 Stationarity test in Bihar rice market

	ADF Statistic	Lag Order	p-value
Mohana	-4.08	4	0.02
	0.48		

A.5 Stationarity tests in Haryana rice markets

	ADF Statistic	Lag Order	p-value
Ellanabad	-3.96	4	0.03
	0.49		
Fatehabad	-3.96	4	0.03
	0.40		
Kaithal	-3.17	4	0.14
	0.42		
Rania	-3.79	4	0.04
	0.52		
Sirsa	-4.28	4	0.01
	0.43		
Tarori	-3.51	4	0.07
	0.38		

A.6 Stationarity tests in Uttar Pradesh rice markets

	ADF Statistic	Lag Order	p-value
Bahraich	-2.56	4	0.35
	0.13		
Basti	-2.75	4	0.27
	0.07		
Chandoli	-1.94	4	0.60
	0.20		
Devariya	-2.90	4	0.21
	0.17		
Gonda	-2.16	4	0.51
	0.16		
Gorakhpur	-3.67	4	0.04
	0.22		
Lakhimpur	-3.94	4	0.02
	0.17		
Lucknow	-2.23	4	0.48
	0.23		
Partaval	-3.23	4	0.11
	0.23		
Pilibhit	-3.41	4	0.08
	0.31		
Shahjahanpur	-3.42	4	0.07
	0.29		
Sitapur	-3.47	4	0.11
	0.61		
Sultanpur	-3.07	4	0.15
	0.29		

A.7 Stationarity tests in West Bengal rice markets

	ADF Statistic	Lag Order	p-value
Bethuadahari	-1.27	4	0.86
	0.26		
Birbhum	-1.72	4	0.69
	0.31		
Bishnupur	-2.30	4	0.45
	0.17		
Bolpur	-2.20	4	0.49
	0.10		
Coochbehar	-2.12	4	0.53
	0.35		
Dinhata	-1.39	4	0.76
	0.81		
Ghatal	-2.13	4	0.52
	0.28		
Kalna	-1.69	4	0.70
	0.14		
Katwa	-2.72	4	0.28
	0.31		
Samsi	-1.89	4	0.62
	0.17		

A.8 Stationarity tests in Haryana pearl millet markets

	ADF Statistic	Lag Order	p-value
Ateli	-2.71	4	0.31
	0.60		
Ballabhgarh	-3.17	4	0.16
	0.51		
Bhuna	-3.74	4	0.07
	0.68		
Fatehabad	-3.94	4	0.09
	0.97		
Hissar	-3.21	4	0.17
	0.67		
Narnaul	-3.75	4	0.08
	0.86		
Narwana	-3.56	4	0.06
	0.47		
Palwal	-2.78	4	0.28
	0.60		
Pataudi	-2.98	4	0.18
	0.22		
Rewari	-3.19	4	0.13
	0.40		
Uchana	-3.41	4	0.13
	0.69		
Uklana	-3.02	4	0.20
	0.51		

A.9 Stationarity tests in Uttar Pradesh pearl millet markets

	ADF Statistic	Lag Order	p-value
Divai	-2.37	4	0.43
	0.14		
Etah	-2.45	4	0.39
	0.32		
Firozabad	-2.05	4	0.55
	0.22		
Haathras	-2.84	4	0.23
	0.15		
Kasganj	-2.63	4	0.32
	0.28		
Khair	-2.17	4	0.51
	0.26		
Mainpuri	-2.47	4	0.38
	0.17		
Sikandraraau	-2.58	4	0.34
	0.21		

A.10 Stationarity tests in Haryana corn markets

	ADF Statistic	Lag Order	p-value
Ballabhgarh	-3.70	4	0.05
	0.49		
Naraingarh	-3.92	4	0.04
	0.57		

A.11 Stationarity tests in Uttar Pradesh corn markets

	ADF Statistic	Lag Order	p-value
Divai	-3.28	4	0.09
	0.23		
Etah	-3.13	4	0.12
	0.14		
Ghaziabad	-3.46	4	0.13
	0.93		
Gonda	-2.99	4	0.18
	0.30		
Jaunpur	-1.18	4	0.90
	0.04		
Kasganj	-3.81	4	0.04
	0.54		
Lucknow	-5.00	4	0.01
	0.70		
Mainpuri	-3.44	4	0.07
	0.32		
Saharanpur	-2.78	4	0.27
	0.42		

A.12 Stationarity tests in West Bengal corn markets

	ADF Statistic	Lag Order	p-value
Kalimpong	-4.54	4	0.01
	0.34		
Samsi	-3.76	4	0.04
	0.38		

Endnotes

[1] Figure 1 was created using GPS Visualizer. http://www.gpsvisualizer.com/

[2] http://cran.r-project.org/web/packages/Amelia/index.html

[3] Full regression results are available by request from the authors.