Rice, wheat, and corn supply response in China

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Abstract

This study analyses the indica rice, winter wheat, and corn production response to prices, rainfall, temperatures, and other parameters for the agriculturally most important provinces in China. System and difference GMM estimators are used as the number of groups is large compared to the time periods and the production response is a dynamic process. We find that all crops strongly respond to prices around planting time and shortly after while prices further away from the time of planting turn out insignificant. Furthermore, rainfall affects the production positively and high temperatures negatively for all crops. The results for other variables differ between the crops. Mixed outcomes are found for irrigation, fertilizer prices, area affected by droughts and interaction terms. Results suggest that irrigation is only partly able to compensate for impacts of weather variability. The presented method for analyzing the price response at different points in time may also be used for general model specification tests.

1 Introduction

Unexpected high and volatile food prices during the 2007-2008 world food crises and thereafter have reemphasized the question of how countries can protect themselves from supply shortages. In view of the various trade restrictions imposed by some major exporting countries, governments tend once again to focus more on self-sufficiency and food storage. China furthermore has to increase its yields due to the rise in population, total grain demand, and meat consumption given the limited possibilities of area expansion.

The primary purposes of analyzing supply response in this paper are threefold. First, identifying different factors that can affect the production, including market prices, biophysical conditions and infrastructures. Second, analyzing differences in these effects between the different crops. Third, analyzing how the predictive power of prices evolves over time and therefore to prices of which point in time farmers react. Hence, a clear understanding of the farmers' planting behavior is needed. Generally in the context of empirical estimation, farmers' decision making process is modeled as a two-step process [Colman, 1983]: First farmers will choose the crop type combing previous weather condition and decide their cropping area based on expectation of the prices they will receive several month later. Second, after planting they will change farmland management measures according to the market prices and weather condition to achieve a high yield. Our focus lies on the production response of winter wheat, indica rice, and corn as these crops are the main staple foods in China. China is the biggest producer of rice and wheat and on of the biggest of corn. The results of the research can also be used as the basis for a short-term forecasting tool for monitoring Chinese food security or as part of a worldwide food availability monitoring tool. However, timely data availability would be needed which usually is not possible for data from the Chinese Agricultural Yearbooks.

In China, early works in this field have investigated the spreading of hybrid rice after the institutional change from a collective team system to a more market-oriented, so-called "household responsibility system" [Lin, 1991]. Decollectivization was found to account for about half of the output growth from 1978 to 1984 while adjustments in procurement prices, in contrast to other market-related reforms, also contributed significantly [Lin,

1992]. However, other results suggest that the household responsibility system was not the main driver of yield increases [Ghatak and Seale, 2001]. Nevertheless, Chinese agriculture was found to respond to prices and price-risks at the national level whereas significant differences at the regional level occurred (ibid.). The next major reform in 2004 included the change from a policy of taxing farm households to providing subsidies. Received by almost all producers, these subsidies are now low per-person but high on a per-area basis [Huang et al., 2013]. Except for the machinery subsidies, which influenced the purchase of machineries, most other grain, input, and seed subsidies were found to not influence area allocation decisions (ibid.). Increased outputs in later years were partly attributed to land reallocation to grain production [Yu and Jensen, 2010]. With the help of a dynamic panel approach, the acreage and yield responses to output prices have been analyzed in a case study for Henan [Yu et al., 2011]. However, evidence from other provinces is missing. On a world-wide level, price volatility, and therefore price risk, was found to reduce the supply response [Haile et al., 2015b]. However, as prices are comparably stable in China, price volatility was not considered as an important factor in this study.

With increasing concerns regarding global warming, its impact to agriculture are among expected to be huge and are already documented. The general findings of these studies are that crop yields will fall in China like those in other developing countries [Tao et al., 2006]. By employing farm-level data and the Ricardian method, the average impact of higher temperatures was found to be negative whereas the average impact of more rainfall was found to be positive [Wang et al., 2009]. Overall, weather conditions, market prices and infrastructures can be seen as the three most important conditions for agriculture production. This study provides an important contribution in evaluating how such weather related variables affect the production of the considered crops on the province level. Furthermore, to our knowledge this is the first study which addresses the response to prices at different periods in time in order to analyze the farmers' price expectation formation process.

2 Data description and usage

Data for acreage, production, output market prices, procurement prices, fertilizer prices, rainfall, consumer price index (CPI), irrigated area, temperatures, sunshine, effective irrigated area, and prices of competing crops were collected from the Chinese agricultural and statistical yearbooks and from the for the years from 1996 to 2012. Province level data was used whenever possible but whenever such data was scare, data on the national level was used. Own crop prices were deflated by the CPI, other prices were deflated by the own crop price to account for possible autocorrelation. Table 1 provides an overview over the aggregation level, frequency, and transformations of the data. The summary statistics of the variables are presented in table 2 for the individual crops.

A panel data set was created for each crop where the provincewise production of a crop is used as dependent variable to be explained by the other variables. The provincial production data, collected from National Bureau of Statistics of China, ranges from 1995 to 2012 and includes 20 provinces planting winter wheat, 29 provinces planting corn, and around 13 provinces planting early and late indica rice while 15 provinces are included with data on middle indica rice. For indica rice, the early, middle, and (double) late

Data	China ... yearbook	Scale	Frequency	Transformation
Production	rural statistic	Province	Yearly	logged
CPI	statistical	Province	Monthly	Continuous CPI build from yearly changes
Total farm crop area	rural statistic	Province	Yearly	-
Irrigated area	water conservancy	Province	Yearly	Devided by total farm crop area and logged
Non-Irrigated area	-	Province	Yearly	log(1 - irrigated area/ total farm crop area)
Wholesale prices	grain	National	Monthly	Devided by continuous CPI and logged
Fertilizer prices	price	National	Monthly	Devided by wholesale price and logged
Rainfall	water conservancy	Province	Monthly	logged
Hours of sunshine	1	Province	Monthly	logged
Lowest temperature	1	Province	Monthly	-
Average temperature	1	Province	Monthly	-
Highest temperature	1	Province	Monthly	-
Area affected by drought	water conservancy	Province	Yearly	Devided by total farm crop area and logged

Table 1: Overview of the data used for the regression analysis. The second column shows the source, i.e. from which of China's yearbooks the data is taken. The 1 means that it is not taken from any yearbook but from the national meteorological information center in China

seasons were pooled in order to get more observations. That way, it could be ensured that the number of observations never falls below 249.

The planting season, complementing and substituting crops may differ slightly in the different provinces. For winter wheat, the planting season is September to October and the harvest takes place in late April or May of the next year. The main substitute is rapeseed, followed by cotton while corn is a complementing crop. Corn is mainly planted during April to June and harvested between August and October. The main substitutes are soybean and cotton and the main complementing crops are wheat and rapeseed. Based on farmers' production behavior, we focus on three aspects factors that is market input and output price, weather conditions and infrastructure. For crop prices, monthly wholesale prices are used. This is justified by the easier availability of wholesale prices compared to farmgate prices and by the high transmission from wholesale to farmgate prices which was reported in the literature [Liu et al., 2012]. As land and labor are limited, the planting behavior can be affected by the price of competing or even complementing crops. Fertilizer prices are chosen as the main input market price. Wages were also included but their time series is short and as a result so is the number of observation. Due to this and the fact that they turned out insignificant, they are not reported in this paper. The agricultural production system is sensitive to weather effects and there are very few measures available to farmers to compensate for such weather effects. Therefore, weather conditions are a very important independent variable in our analysis. We have temperature, rainfall and sunshine provincial and monthly data from the national meteorological information center in China. In addition, the yearly area affected by drought on a provincial level were collected there and used as fraction of area affected by droughts to see the weather

	Observations	Mean	SD	Min	Max
Corn					
Production (1000 tons)	552	458.68	549.54	0.89	2675.80
June WSP (CNY/kg)	465	1.42	0.40	0.87	2.32
Irrigation (1000 ha)	589	1810.98	1400.49	144.20	5342.12
Rainfall@growing (mm)	690	14.53	12.91	1.46	301.04
A-temp@growing (°C)	690	298.86	3.47	285.29	304.85
Drought area (1000 ha)	499	445.08	543.03	1.00	3133.00
Fertilizer price (CNY/kg)	496	1915.06	670.66	1186.00	3140.00
Winter wheat					
Production (1000 tons)	360	464.3	686.8	0.2	3177.4
March WSP (CNY/kg)	330	1.5	0.4	1.0	2.2
April's sunshine hours	506	5.6	1.9	1.7	9.4
Irrigation (1000 ha)	418	1939.5	1458.5	153.0	5205.6
Rainfall@growing (mm)	506	6.3	4.9	0.2	25.3
H-temp@flowering (°C)	506	300.5	4.3	290.7	311.5
Rainfall@planting (mm)	506	3.6	5.1	0.1	105.1
Drought area (1000 ha)	352	377.2	470.1	1.0	2573.0
Fertilizer price (CNY/kg)	352	1879.4	662.3	1184.0	3000.0
Indica rice					
Production (1000 tons)	707	406.1	433.0	0.0	2161.1
WSP@planting (CNY/kg)	1395	1.5	0.4	0.9	2.5
Sunshine hours@planting	2139	6.4	1.7	1.5	10.7
Irrigation (1000 ha)	1767	1811.0	1399.7	144.2	5342.1
Rainfall@growing (mm)	2139	7.8	6.6	0.2	196.0
Rainfall@planting (mm)	2139	3.0	4.4	0.1	105.1
H-temp@growing (°C)	2139	306.2	3.5	295.7	316.7
Drought area (1000 ha)	1497	445.1	542.7	1.0	3133.0
Fertilizer price (CNY/kg)	1488	1895.8	677.8	1126.0	3340.0

Table 2: Summary statistics of the data from all provinces. Data which is only available on a national basis has been copied for all provinces and therefore is shown to have more observations than it actually has on the national level.

effect on production. We use the percentage of irrigated cultivated area as a measure of infrastructure and technology and imputed missing values for this variable (not for any others). Irrigation also allows to compensate for shortfalls in rainfall and partly even droughts. As irrigation is always used in combination with the application of chemical fertilizers, it represents a higher standard of agricultural infrastructure. In order to see the production's response to the weather variables at different times during the planting, growing, and harvesting period, we test the influence of these variables during several important months. As some of weather data has a high level of autocorrelation, it is not possible to include every month in econometric analysis. Therefore, only the most important month is included or, for the rainfall, the sum of the most important months is calculated.

Here are some of our hypotheses to test:

1. We expect that own-prices have a positive effect on production, and prices of competing crops have a negative one. Fertilizer prices are usually expected to have a negative effect on production but for crops which need relatively little fertilizers compared to others, the effect may be reverse as high fertilizer prices may incentive planting these crops.

2. The prices around planting time are expected to have the biggest impact on the production. Prices one to three month before planting will influence the area allocation decision while prices at planting and during the growing season may affect how farmers take care of their fields, e.g. by applying fertilizers or pesticides, watering their plants, and other management practices which influence the yields.

3. Droughts have negative effect on production.

4. Irrigation has a positive effect on production and it can reduce the negative impact from adverse weather. Such adverse weather effects may include low rainfall or very high temperatures.

There are some limitations of this approach. The biggest limitation might be the aggregation level of data. Some price data are only available on a national level but as price transmission within Chine is usually large, this might not be a big problem[Huang and Rozelle, 2006]. But for the biophysical variables, even though they are available at the provincial level, this aggregation might be more problematic as rainfall, hours of sunshine, or temperatures may vary in different parts of the same province. Therefore, we are likely to underestimate the influence of these biophysical variables do to the high level of aggregation. Furthermore, important variables may not be considered which can be an issue if they fluctuate a lot in the short term. If instead they mostly consist of a long term trend, then they will be captured by the orthogonal deviations as well as by the lagged production and, as a result, will not cause any problems.

3 Methodology

Strictly speaking, the farmer's decision making process consist of two steps, the area decision, and the yield decision [Colman, 1983]. The considered variables are mostly the same but may differ slightly as, for example, competing crop prices are not that important after the area decision was made. However, they still may be important because they may affect the input allocation decision for fertilizers, pesticides, water and other variables. On the other hand, not all variables which influence the yields also matter for the are allocation. Unexpected rainfall shocks after planting cannot be anticipated and therefore cannot affect the area decision but may affect the farmer's fertilizer application and therefore the yield. Therefore, modeling the production is a combination of the area and yield processes and only allows investigation a sum of the affects of the two. Nevertheless, it is important to see the combined effects as in the end we care about the total production volume and want to know which variables have an influence and in which way. Another reason to look at the combined effect on production is that statistical issues arise when looking at area

and yield separately as they influence one another and therefore one has to deal with this additional endogeneity.[1]

The Arellano-Bond difference GMM and system GMM estimators [Holtz-Eakin et al., 1988, Arellano and Bond, 1991, Arellano and Bover, 1995, Blundell and Bond, 1998] are used for a number of reasons. Firstly, the time period is rather short, usually around 14 years, while the number of observations per time period is comparatively large, ranging from 20 for wheat over 29 for corn to around 40 for rice. The difference and system GMM estimators control for such dynamic panel bias. Secondly, the production response is a dynamic process, i.e. current realizations depend on past ones. Thirdly, fixed effects across groups allow for a heterogeneity of these. Finally, idiosyncratic disturbances may have individual-specific patterns of heteroskedasticity.

For all three crops, three different specifications are shown which differ in the variables which are considered. Including more variables allows controlling for more factors but also decreases the degrees of freedom, the significance of variables which are strongly correlated and even the number of observations as many variables could only be obtained for a limited amount of years. Comparing the different specifications also allows checking the consistency of the estimations as huge deviations, such as the same variables sometimes being positive and significant and at other times negative and significant, would indicate a model misspecification. For all three specifications, the results for both system as well as difference GMM estimations are shown. In general, we think that the difference GMM estimator might be more appropriate as it cannot be ruled out that first differences of the instrument variables are uncorrelated with the group fixed effects. This hypothesis shall be supported by our findings as will be seen in the next chapter. The Windmeijer finite-sample correction for standard errors is used [Windmeijer, 2005]. We use the xtabond2 command in Stata which is written by David Roodman and follow the application guidelines in his accompanying paper [Roodman, 2009]. Instead of first differencing, forward orthogonal deviations are used [Arellano and Bover, 1995, Roodman, 2009], i.e. the average of all available future observations is subtracted. These remove fixed effects, just like differencing, but because lagged observations are not used, these remain orthogonal to the transformed errors. That way, the number of observations will not be reduced by gaps in the dataset. As suggested, time dummies for all years are included in all model specifications (ibid).

For proper usage of the GMM techniques, a number of test need to be run to check the consistency of the estimations (ibid.). The joint significance of the variables is evaluated with an F-Test for which we expect the p-value to be clearly below 0.1 (ibid.). While the first lagged residuals are expected to be correlated (AR1$<$0.1), the twice lagged residuals must not (AR2$>$0.1) [Arellano and Bond, 1991]. Considering the null hypotheses, this means the p-value of the AR1 has test in the result tables to be smaller than 0.1 while the p-value for AR2 must be higher than 0.1 (for significance at the 10%-level). Furthermore, the Hansen-J test allows checking if the model specification and all over-identifying restrictions are correct [Baum, 2006]. It is suggested that the p-value should be above 0.25 but at the same time not perfectly match 1 for this test [Roodman, 2009]. The difference-in-Hansen test is used to investigate the exogeneity of instruments. The null hypothesis is that they are exogenous, so to not to reject the hypothesis the respective p-values have to be above 0.1. The number of instruments were chosen to provide robust

[1] Yet, in a later stage it is planned to additionally include the area and yield decisions in this paper.

test statistics. There are no clear rules about how many instruments are appropriate. However, the number of instruments should always clearly be lower than the number of observations which is the case for all our specifications. All the test statistics were fulfilled in all specifications except for the first two specifications for winter wheat, which fail to reject the second order autocorrelation at the 10% level but nevertheless do so at the 5% level, and the second specification for indica rice which fails to reject the Hansen-J test and the difference-in-Hansen test.

Apart from evaluating the production response with price at a predetermined point in time, we are interested in seeing how the price response when using prices at different points in time. Therefore, the regressions are conducted with prices at different months before and after planting (from 20 month before up to 20 month after planting) and it is graphically illustrated how this changes the results.

Fore indica rice, the three different seasons were pooled together. Hence, there is no fixed planting month but instead depending on the season, the appropriate planting month was chosen. All the other variables are also chosen relative to the month of planting for that season in that province. This means, for example, that the planting time price is April for early, Mai for middle and July for late indica rice. Similarly, rainfall during the growing season considers April and Mai for early indica, May and June for middle indica, and July and August for late indica rice.

All variables were logged and therefore the effects can be interpreted as elasticities. The only exception are the temperatures which exhibit also negative values and are more intuitive to interpret in their non-logged form.

4 Results

The results for the production of corn are shown in table 3, for winter wheat in table 4, and for rice in table 5.

The results for corn, illustrated in table 3 show that all of the six specifications seem to be valid specifications based on the provided test statistics. A significant amount of the variation in production is explained by last years production (which also accounts for unobserved variables), ranging from 0.772 to to 0.956. All of them are significant at the 1% level. The wholesale price in June turns out to be also always highly significant and has a major contribution regarding its elasticity of around 0.2. This implies that a 1% increases in prices will lead to a 0.2% increase in production which seems reasonable and is comparable to other studies. The fraction of irrigated area is only significant in two specifications but has a huge impact in these. Indeed, it is only significant for the difference GMM specifications where the interaction terms are included which could possibly be attributed to a collinearity in these variables (their correlation coefficient is -0.79 for corn, -0.17 for wheat and -0.46 for rice). In addition, the total effect of irrigation is the elasticity of irrigation multiplied by the interaction term of irrigation times the average temperature and this interaction term takes the value of -20.69 at the sample mean. Despite its need for rainfall during the growing season, we cannot find any effect of this variable on the corn production. In contrast, high average temperatures during the growing season which is in mid-summer have a small but significant negative impact. When interacted with the non-irrigated area, i.e. the fraction of the agricultural area which is not irrigated, we find

	(1)	(2)	(3)	(4)	(5)	(6)
L.Production	.949***	.807***	.954***	.772***	.956***	.902***
	(.05)	(.166)	(.047)	(.143)	(.034)	(.143)
WSP June	.202***	.296***	.184**	.291***	.177***	.226***
	(.069)	(.077)	(.067)	(.055)	(.051)	(.067)
Irrigated	-.055	-.115	4.69	20.2**	1.61	16.9**
	(.049)	(.131)	(5.78)	(8.15)	(6.61)	(8.05)
Rain@growing	-.032	-.059	6.3e-03	-.013	-7.4e-03	-.076
	(.029)	(.063)	(.035)	(.06)	(.033)	(.083)
A-Temp@growing	-.016***	-.029*	-.034	-.095***	-.014	-.058**
	(4.2e-03)	(.015)	(.022)	(.026)	(.023)	(.028)
Drought area	-.027**	-.032***	-.027**	-.033***	-.014	-.035***
	(.01)	(8.6e-03)	(.011)	(9.1e-03)	(.013)	(.01)
Non-Irrigated			.046*	.077*	.066***	.071*
X Rain@growing			(.023)	(.045)	(.02)	(.039)
Irrigated X			-.016	-.067**	-5.4e-04	-.052*
A-Temp@growing			(.019)	(.027)	(.022)	(.027)
Fertilizer@planting					-.231***	-.203**
					(.066)	(.076)
Irrigated X					-.191***	-.182**
Fertilizer@planting					(.058)	(.071)
Substitute@planting					6.4e-03	.018
					(.018)	(.025)
Constant	4.95***		10.4		6.31	
	(1.34)		(6.49)		(6.87)	
Estimator	system	difference	system	difference	system	difference
Groups	29	29	29	29	29	29
Instruments	29	27	31	29	30	28
p:F-Test	3.0e-24	1.7e-19	8.0e-29	1.3e-23	3.2e-37	1.3e-27
p:AR1	8.6e-05	1.5e-03	9.3e-05	1.1e-03	3.2e-04	1.1e-03
p:AR2	.591	.919	.571	.685	.581	.949
p:Hansen-J	.361	.291	.403	.326	.535	.286
p:Diff-Hansen	.653	.812	1	.9	1	.436
Observations	413	384	413	384	325	296

Standard errors in parentheses

WSP=Wholesale price; X indicates interaction terms; A-Temp=average temperature

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Results for corn production response with System and Difference GMM for three different specifications.

that rainfall during the growing season becomes significant. It then has, as expected, a positive influence on production, even though a small one only. When interacted with irrigation, high average temperatures area negative and significant for the difference GMM specification. Therefore, they seem to negatively influence the benefits from irrigation. In contrast to our expectations, however, we cannot find that irrigation may help to compensate high average temperatures. As expected, the drought area has a significant and negative influence in all but one specifications. High fertilizer prices at planting time reduce the total production and again, this effect seems to be more pronounced provinces

	(1)	(2)	(3)	(4)	(5)	(6)
L.Production	.951***	.951***	.97***	.951***	.964***	.96***
	(.032)	(.104)	(.036)	(.11)	(.063)	(.087)
H-Temp@flowering	-.037**	-.043***	-.028*	-.044**	-.037	.061
	(.014)	(9.6e-03)	(.016)	(.019)	(.122)	(.123)
Sun@flowering	.327**	.156	.185	.081	.196	.124
	(.152)	(.092)	(.199)	(.205)	(.293)	(.207)
Rain@planting	.048**	.054**	.046*	.045	.047	.04
	(.023)	(.021)	(.023)	(.026)	(.037)	(.042)
Rain@grow	-.014	3.5e-04	-.046	-.045	-.133	-.143
	(.052)	(.032)	(.037)	(.037)	(.091)	(.099)
Irrigated	-.305*	-.055	-.281*	-.344	-.095	-32
	(.15)	(.483)	(.155)	(.478)	(26.5)	(37.3)
Drought area	-.038***	-.037**	-.025*	-.026	-.026*	-.034
	(.011)	(.014)	(.014)	(.016)	(.014)	(.02)
WSP March			.268**	.338***	.255*	.292**
			(.128)	(.116)	(.143)	(.132)
Non-Irrigated					-.177	-.137
X Rain@growing					(.165)	(.135)
Irrigated X					-1.1e-03	.105
H-Temp@flowering					(.089)	(.125)
Constant	10.4**		7.9		10.4	
	(4.13)		(4.65)		(36.1)	
Estimator	system	difference	system	difference	system	difference
Groups	20	20	20	20	20	20
Instruments	28	26	27	25	29	27
p:F-Test	1.9e-21	1.4e-13	9.0e-22	2.0e-12	1.8e-22	2.0e-14
p:AR1	7.0e-03	8.8e-03	.012	.019	.016	.012
p:AR2	.065	.053	.115	.185	.241	.173
p:Hansen-J	.523	.595	.676	.463	.744	.805
p:Diff-Hansen	1	.949	1	.847	1	1
Observations	300	280	269	249	269	249

Standard errors in parentheses

WSP=Wholesale price; X indicates interaction terms; H-Temp=high temperature

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results for winter wheat production

with a high share of irrigated area. This may be due to the usually much higher lever of fertilizer application on irrigated areas which may be over-proportionally affected. Prices of competing crops turn out insignificant.

For winter wheat, shown in table 4, the last year's production is again the most important driver and consistently significant at the 1% level. Wholesale prices in March have a similar positive and significant effect as for corn. The elasticity is around 0.29 and hence even slightly larger than for corn. The first two specifications do not include any prices in order to see if there are any changes when more observations are included. Indeed, sunshine at flowering (around two month before harvesting) does have significant and positive influence only in the first specification. From the literature, we expect wheat to

	(1)	(2)	(3)	(4)	(5)	(6)
L.Production	.936***	.913***	.938***	.914***	.879***	.778***
	(.062)	(.07)	(.055)	(.055)	(.065)	(.112)
WSP@planting	.249**	.196***	.175***	.181***	.264**	.163**
	(.093)	(.067)	(.054)	(.054)	(.098)	(.061)
Rain@growing	.086*	.053*	.336	.152	.5*	.115
	(.046)	(.027)	(.24)	(.139)	(.253)	(.178)
Sun@growing	.099	.174***	.06	.167***	8.7e-03	.142*
	(.084)	(.061)	(.07)	(.05)	(.102)	(.074)
H-Temp@growing	7.9e-03	-.024**	.011	-.026***	.028	-.039***
	(.014)	(.01)	(.013)	(8.5e-03)	(.027)	(.013)
Irrigated			.826	.356	1.28*	.323
			(.698)	(.521)	(.688)	(.674)
Non-Irrigated			.604	.294	.861*	.262
X Rain@growing			(.5)	(.287)	(.484)	(.346)
Drought area			-4.3e-03	-4.9e-03	6.1e-03	-1.4e-03
			(.01)	(8.8e-03)	(.011)	(8.0e-03)
Fertilizer@planting					8.3e-03	.032
					(.071)	(.078)
Substitute@planting					.051	.018
					(.044)	(.032)
Constant	-2.57		-2.6		-7.51	
	(4.25)		(3.82)		(8.08)	
Estimator	system	difference	system	difference	system	difference
Groups	41	41	39	39	39	39
Instruments	22	20	25	23	24	22
p:F-Test	3.0e-23	2.8e-16	8.2e-31	3.2e-20	4.4e-23	1.2e-15
p:AR1	.073	.073	.093	.098	.091	.118
p:AR2	.195	.174	.184	.171	.124	.142
p:Hansen-J	.285	.153	.43	.341	.608	.409
p:Diff-Hansen	.967	.088	.704	.102	.353	.227
Observations	589	548	542	503	433	394

Standard errors in parentheses

WSP=Wholesale price; X indicates interaction terms; H-Temp=high temperature

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Results for indica rice production (different seasons are pooled)

need a lot of sunshine during this period [FAO, 2015]. Furthermore, a lot of rain is needed during and shortly after planting as well as during the flowering and yield formation (ibid.). The positive influence af rainfall during and after planting can be observed in the regression and is significant in three specifications. However, the rainfall during the growing season is always insignificant as well as its interaction term with the non-irrigated area. This might be a result of the data aggregation as explained above. Surprisingly, the irrigated area seems to have a negative effect even though it is only significant at the 10% level and only in two specifications. The underlying reason could be that farmers change for more profitable but water-dependent crops once they have irrigation available. The drought area again has a significant negative impact in most specifications, again with a

very small effect though. The expected negative effect of too high temperatures during flowering time vanishes once the interaction term with irrigation is included. Then, both terms are insignificant. Fertilizer prices and prices of competing crops have no significant effect but reduce the number of observations significantly. Therefore, they are not shown separately but are available upon request.

Similar to corn and wheat, the lagged production is the most important driver for the indica rice production as illustrated in table 5. The effect of the wholesale price is similar to the case of corn, it is always significant and has an affect size of around 0.2. Rain during the growing season, of which rice needs a lot in order for the areas to be flooded, is positive but only significant at the 10% level in half of the specifications. But as explained before, this might be a result of aggregating rainfall data on provincial levels. When interacted with the non-irrigated area, only in one of four specifications we find this interaction to be significant and it only is at the 10% level. The same holds for the irrigated area itself which is consistently positive but only significant in this once specification. For the sunshine, we find that a 1% increase in the number of hours of sunlight increases the production by around 0.16% in all the difference GMM specifications but only in those. Similarly, the damaging effect of too high temperatures during the growing season can be observed in the difference GMM specifications only but is consistently present in those. The drought area, fertilizer prices and the prices of competing crops all turn out insignificant. The underlying reasons might be that the costs of switching are higher for rice, that rice needs comparatively little fertilizer per unit of output, or that the data is too aggregated to observe any effect.

Overall, our results are mostly comparable to what other studies have found. In a non-crop specific analysis Ghatak et al. find a price elasticity between 0.174 and 0.394 [Ghatak and Seale, 2001] which is similar to ours. Looking at the national level only, own price elasticities of 0.23 for rice, 0.052 for wheat, and 0.164 for corn have been reported [Haile et al., 2015a]. Our results for rice and corn are comparable whereas we find a higher price response for wheat. For Henan, Yu et al. found no significant response for wheat but a surprisingly high elasticity of 0.737 for corn [Yu et al., 2011]. However, the elasticities of competing crop prices are also high and significant. They also report that rainfall increases winter wheat production[2].

As explained in the section on the methodology, we want to analyze how the production reacts to prices at different points in time. Therefore, the regressions with same specifications were run for prices at different month before and after the planting time. For all the other variables the same values as before were used. For wheat and corn, specifications 3 and 4 were used therefore while specifications 5 and 6 were used for indica rice. For each crop, these seem to be the specifications with the highest explanatory power. We only show how the p-value of the price variable changes over time but inspection of the test statistics indicates that the specifications are valid for the different points in time. Figures 1, 2, and 3 show the results for corn, winter wheat, and indica rice, respectively. On the x-axis are the month before or after planting while the y-axis shows the p-values from 0 to 0.2 at which the figures are cut off. Both the System-GMM as well as the Difference-GMM results are shown. We find that in general, the curves follow an U-shape which is what we expect. Prices far before or after planting do not have any explanatory power. However,

[2]Multiply the area times the yield effect

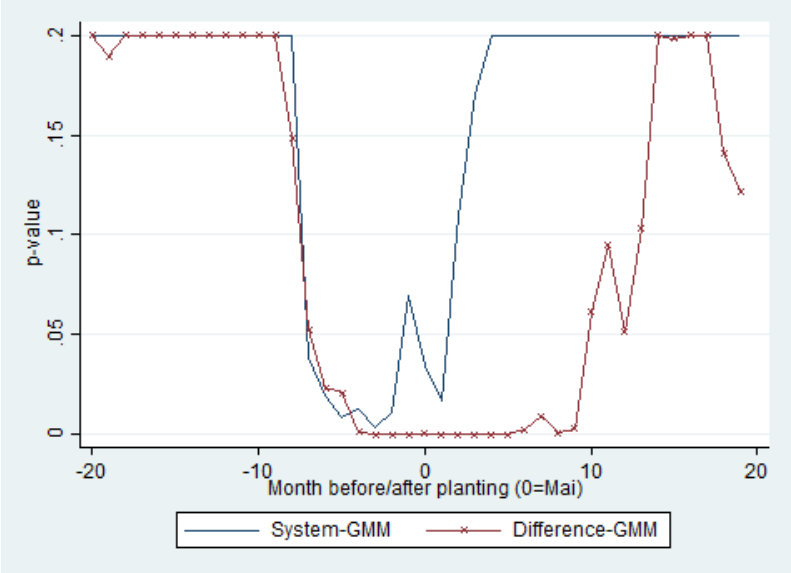

Figure 1: Corn production: Explanatory power of the wholesale prices over time

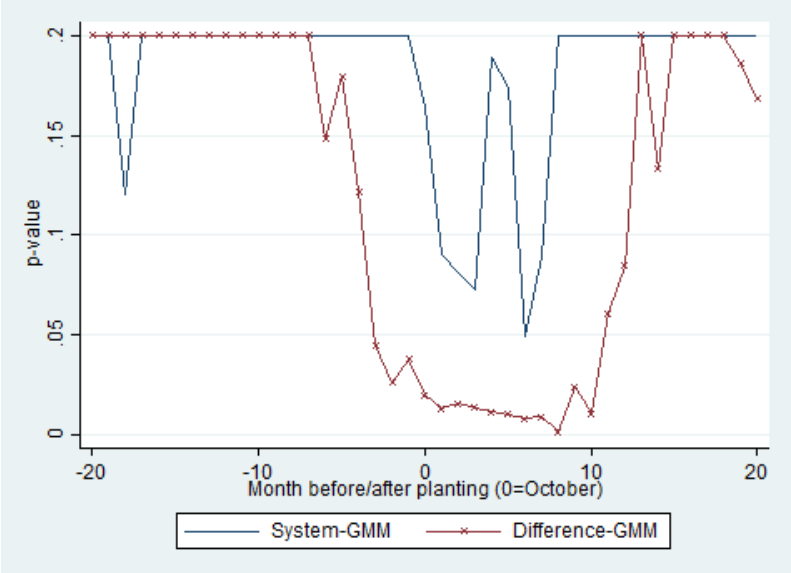

Figure 2: Winter wheat production: Explanatory power of the wholesale prices over time

prices around planting time are usually highly significant. As explained before, we expect the Difference-GMM estimator to perform better. This hypothesis is supported by the graphs. The fluctuations of the System-GMM results are much higher, particularly for winter wheat and indica rice. In general, the period up to which prices are significant extents further after planting for the Difference-GMM while in the case of winter wheat it also starts earlier before planting. Prices after harvest are of course influenced by the production and this additional endogeneity may lead to non-robust results after harvesting.

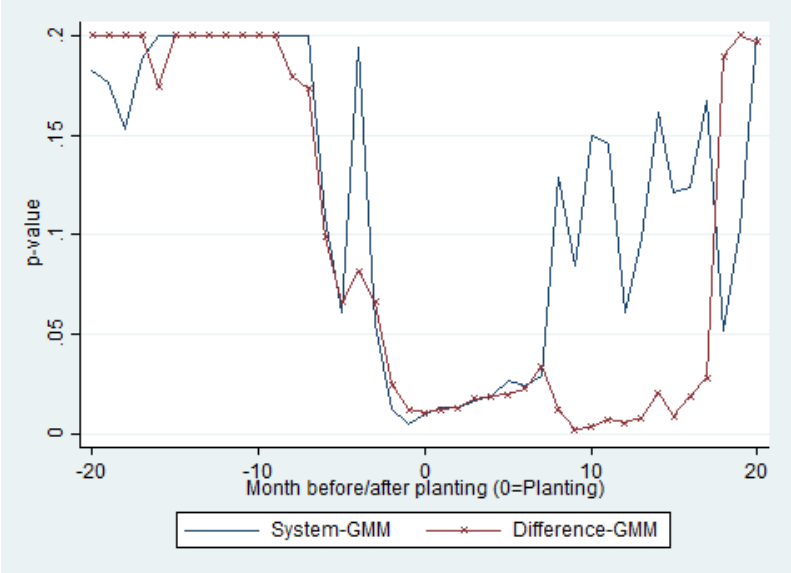

Figure 3: Indica rice production: Explanatory power of the wholesale prices over time

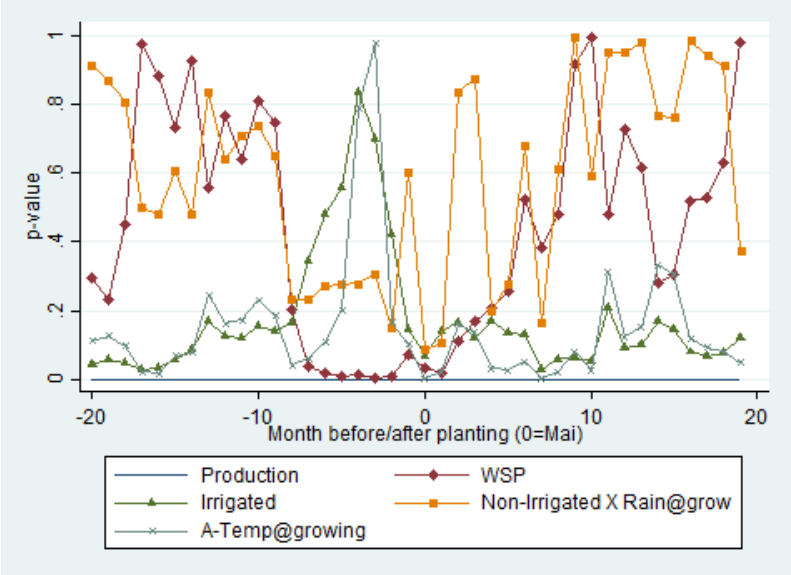

Figure 4: Model robustness check for the corn production regressions using the System-GMM estimator

Comparing the different corps, we find that farmers seem to react earlier to corn prices than to winter wheat and indica rice prices. While, as shown above, the elasticity is the largest for wheat, the response is more significant for corn and rice with the latter lying in the middle of the former two. For all crops, prices remain highly significant for a while after planting which indicates that not only the area, but also the yield responds to prices, may it be due to fertilizer or pesticide application, irrigation, or other ways. Further analysis to get a more clear picture of this process requires to separately look at the area

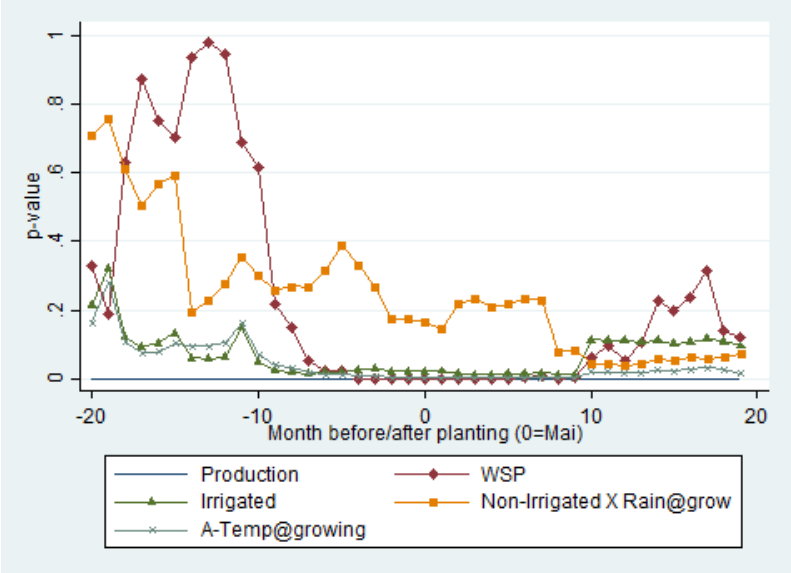

Figure 5: Model robustness check for the corn production regressions using the Difference-GMM estimator

and yield response which is planned for a later stage of this research. A clear result of this analysis is, that farmers, at least on average, do not look at last year's planting or harvesting prices but indeed consider current prices around planting time to be the more important.

This method of investigating the prices at different points in time may also be used for general model specification test. For a robust model, we expect the significance of the tested variables to consist of low-frequency components implying that there are only slow and smooth changes and no big short-term fluctuations. The occurrence of big fluctuations, in particular if some variables consistently change between not significant and significant, suggest that the specification is not robust. Figures 4 and 5 show the p-values of the same regression results as before for the System and Difference-GMM estimation for corn, respectively. This time, some of the other variables were included[3] We find that in the Difference-GMM specification the p-values of all variables only change very slowly over time (consider the different scale of the y-axis). In contrast, the fluctuations of all variables are more pronounced for the System-GMM estimation. This supports our hypothesis that the Difference-GMM estimator is more appropriate. However, the fluctuations still seem to be mostly on an acceptable level; for problematic specifications much higher fluctuations are expected. Interestingly, prices around 2 to 5 months before planting time seem to have such a high explanatory power in the case of the Sytem-GMM, that all other variables apart from the lagged production become insignificant. This is an indication that prices before planting might be the most important one for the final production. Looking separately at the area and yield response will allow to shed more light on this issue.

[3]Not all variables were included because this would reduce the recognizability of the figure too much.

5 Conclusion

The corn, winter wheat, and indica production response for the main agricultural provinces were estimated using the System- and Difference-GMM estimators. Our major findings include: (1) All crops response strongly to prices at planting time, (2) the effect of the price response is similar for rice and corn while it is slightly larger for winter wheat, (3) rainfall is important, for corn in particular on non-irrigated areas and, as for wheat, during the growing season whereas for rice it is important during and shortly after planting, (4) high temperatures negatively influence production which may become problematic considering possible future impacts of climate change, (5) irrigation may partly help to overcome shortfalls in rainfall but not compensate for the negative effects of high temperatures, (6) a negative impact of fertilizer prices was only found for corn, (7) prices shortly before and after planting have a very high explanatory power while prices further away from planting do not; this also implies that farmers, at least on average, respond to current prices and not to last year's planting or harvesting prices. In general, the Difference-GMM estimator seems to perform better than the System-GMM estimator. Our method to analyze the importance of prices at different points in time may also be used to test the general robustness of any type of model using data which is available at a sufficiently high frequency.

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