Effects of weather shocks on wheat prices in Central Asia

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Abstract

Higher weather volatility may be reflected in higher incidences of weather shocks. Weather shocks could potentially affect the supply of agricultural commodities and their prices. In this study, the effects of weather shocks on agricultural commodity prices in Central Asia are investigated at the provincial scale using monthly data for the period of 2000-2010. The study uses an estimation method, where the idiosyncratic components of the variables are analyzed using Feasible Generalized Least Squares (FGLS) panel regression in the presence of cross-sectional dependence and serial autocorrelation. The analysis indicates that weather volatility and, especially, the fluctuations in the availability of irrigation water have statistically significant effects on wheat prices in Central Asia. Weather shocks, involving lower than usual temperatures and precipitation amounts, could create favorable conditions for higher wheat prices in the region.

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1. Introduction

Weather shocks are considered to be one of the important sources of variability in agricultural commodity prices (Gilbert and Morgan, 2010). Although there is no evidence that weather shocks alone have played a major role in the food price spikes in 2008 (Headey & Fan, 2008), it seems, however, that they have contributed to the price spikes in interaction with other factors (Mitchell, 2008; von Braun and Tadesse, 2012). Climate change is likely to increase weather variability and incidences of extreme events (IPCC, 2012), potentially leading to growing impacts of weather shocks on agricultural and food price (Torero and von Braun, 2010; von Braun et al., 2008). This may have considerable influence on poverty levels and economic performances of developing countries dependent on agricultural and agro-food sectors, especially if they are net food importers. Most of the existing research on the impacts of weather shocks on agricultural prices studies earlier historic periods and there are only few studies covering more recent periods (Burgess and Donaldson, 2010; Fox, Fishback, and Rhode, 2011; Jolejole-Foreman and Mallory, 2011; Roll, 1984; Solomou and Wu, 1999). Arguably, this lack of research attention is perhaps influenced by the fact that modern farm management techniques and more globalized agricultural markets have noticeably reduced the impacts of weather shocks on agricultural prices, especially in developed countries. Even in developing countries, generally more vulnerable to weather shocks, a major research concern has been with market integration and price transmission effects *per se*, without specific attention to weather impacts. Climate change and related increases in the frequencies and magnitudes of weather shocks are likely to necessitate a paradigm shift towards increasing research efforts on the effects of weather shocks on agriculture and agricultural prices, especially in developing countries.

Therefore, the main purpose of the present study is to advance the current knowledge through three contributions. First, the agricultural price transmission is linked to specific weather variables such as temperature and precipitation, and availability of irrigation water. The previous literature on the interaction of weather shocks and agricultural prices did not link price transmission to specific marginal changes in these variables. Second, an innovative, yet straightforward, method of assessing the impacts of weather shocks on agricultural commodity prices is suggested exploiting the idiosyncratic components of variables in a long panel setting. This approach allows for disaggregating short-term shocks in prices from long-term trends, thus providing a theoretically consistent way to estimate the effect of weather shocks on agricultural prices. And third, a focused treatment of transmission of weather shocks on agricultural prices is provided by using more recent contemporaneous data. In spite of these contributions, the present research has certain limitations, the key among them being its inability to distinguish between varying responses of public and private stockholders to weather and price shocks due to data constraints. Data limitations also concern commodity stocks and prices, as they were not always available at the needed scales and frequencies.

2. Relevant Literature

The study of price dynamics in economic literature has been framed within two competing theories providing alternative explanations of price formation, namely: the cobweb model of adaptive expectations (Cochrane, 1958; Ezekiel, 1938; Nerlove, 1958) and the rational expectations model (Muth, 1961). The cobweb model posits that prices are formed by endogenous factors, namely, forecasting errors. For example, in response to high prices of a particular crop farmers increase their production which leads to lower prices for this crop in the next period. Responding to these lower prices, farmers reduce their production of this crop in the second period, only to see the rising prices in the third period as a result of this supply reduction, and so on (Barré, 2011). The second model assumes that economic agents rationally use all the available information and price dynamics are caused by exogenous factors, especially weather shocks (ibid.). These two approaches also differ in the solutions they propose for tackling price volatility. The rational expectations approach advocates methods that allow for spreading the risks among a larger number of economic agents such as insurance schemes, temporal and spatial arbitrage, including storage and free-trade policies. In contrast, the measures proposed by the cobweb approach for price stabilization usually involve production quotas and other Government interventions for managing the commodity supply within the country (Mitra and Boussard, 2012).

Both models were extended over time to account for their shortcomings. Nerlove (1958) extended the original cobweb model developed by Ezekiel (1938) and suggested that economic agents form their price expectations based on both the current prices and also their forecasting errors made during the last periods, i.e. they try to learn from their mistakes. Later on, the model was extended to include risk aversion (Boussard, 1996) and non-linear curves (Hommes, 1992). In spite of these improvements, Deaton and Laroque (1996) point out that the cobweb model still cannot reconcile its predicted negative first order autocorrelation in prices with the empirical evidence showing positive autocorrelation (Barré, 2011). The key implication of the rational expectations model is that economic agents do not make systematic forecasting errors. However, this would imply stationarity of price series around a steady state, which is against the empirical findings of non-stationarity of most commodity price series. To account for this shortcoming, Barré (2011) informs that competitive storage model was developed to explain positive autocorrelations in prices (Muth, 1961), as well as their kurtosis and positive skewness (Deaton and Laroque, 1992). Frankel (1986) extended the competitive storage model by adding the overshooting hypothesis, which links the price dynamics in the commodity markets to changes in the monetary policy. Deaton and Laroque (2003) showed that it is also possible to represent positive autocorrelation, skewness, and kurtosis of observed data series with a rational expectations model without competitive storage. Other major challenges in empirical estimations are non-linear components, structural breaks or regime shifts.

In this larger context, the strand of literature that considers the impact of weather shocks on prices is relatively thin. Roll (1984) finds that cold weather shocks in central Florida, where virtually the entire US orange production occurs, affect the futures prices of frozen concentrated orange juice, though cold weather shocks seem to explain only a small share of the futures price variation. Webb, von Braun and Yohannes (1992) find that the upward effect of droughts on food prices in Ethiopia during 1980s was strongly exacerbated by infrastructural and administrative constraints to spatial arbitrage. Solomou and Wu (1999), in their comparative study of the effects of weather shocks on agricultural prices in Britain and Germany between 1870 and 1913, conclude that weather shocks had larger impacts on the German economy, because Germany was more dependent on agriculture, and German agriculture was more protected than British agriculture operating under virtually free trade conditions. Similarly, using historic data on weather and crop prices for the US during 1895-1932 under "unfettered" agricultural commodity markets, Fox, Fishback and Rhode (2011) find that local weather did not have a significant effect on the prices of internationally traded crops, namely, cotton and wheat. However, weather shocks significantly influenced the prices of maize and hay, which were mostly locally consumed. Burgess and Donaldson (2010) indicate that openness to trade and better transport infrastructures (construction of railroads) in colonial-era India lowered the vulnerability of agricultural prices and incomes to rainfall shocks, and also dramatically reduced the incidences of famines. Jolejole-Foreman and Mallory (2011) show that positive rainfall shocks are associated with higher margins between farm-gate and retail prices, and reduced imports of rice in the Philippines.

Efficient price transmission between spatially separated markets and unhindered opportunities for spatial arbitrage (law of one price) are believed to lead to more competitive markets and hence more efficient allocation of resources and long-run growth (Samuelson, 1952; Takayama and Judge, 1964). Better market integration can allow for mitigating the impacts of weather shocks on local agricultural prices. Market integration may also reduce the need for food self-sufficiency (Fafchamps, 1992). Several factors such as trade barriers, subsidies, exchange rate policies, poor infrastructure and non-competitive market structure are believed to impede price transmission (Rapsomanikis, Hallam, and Conforti, 2003).

Methodologically, the early research on price transmission was based on examining bivariate correlation coefficients of prices in different markets, where high correlation coefficients were regarded as a sign of price transmission (Rapsomanikis, et al., 2003). Another widely used approach was regressing the prices on each other, where coefficients closer to unity would imply a stronger co-movement of the prices (Mundlak and Larson, 1992). Ravallion (1986) suggested an improved approach which also incorporated price lags in the regression analysis thus enabling to segregate short- and long-term price transmission effects, and relaxing the assumption of instantaneous adjustments in different markets. Webb, von Braun and Yohannes (1992) have further nuanced the notion of price co-movements in different markets, in the example of food prices in Ethiopia, indicating that these co-movements could be caused by covariate weather shocks even in the absence of market integration. Non-stationarity of much of the time series data and invalid tests of statistical significance resulting from applying simple regression techniques led to the development of the Error Correction Model (Engle and Granger, 1987), which were later advanced to the Vector Autoregressive Model (VAR) and the Vector Error Correction Model (VECM). Non-linear aspects of price adjustments led to development of the Asymmetric Error Correction Model (Granger and Lee, 1989) and threshold co-integration models (Enders and Granger, 1998). Von Cramon-Taubadel (1998) applied the cointegration methods to testing for asymmetric price transmission, thus accounting for non-stationarity of price time series. Von

Cramon-Taubadel, Loy, and Meyer (2003) also highlight the importance of the level of aggregation in price series while testing for asymmetric transmission. In their analysis of retail and wholesale prices of chicken and lettuce in Germany, Cramon-Taubadel, Loy, and Meyer (2003) use weekly individual store prices and average retail prices during 1995-2000 and find that the individual store data reveals asymmetric price transmission, whereas the aggregated average retail price series do not show any sign of asymmetry. Relatively more recently, switching regime models and dynamic panel causality models were applied to test for price transmission.

3. Conceptual Framework

The theoretical model follows the rational expectations approach to price transmission which assumes that exogenous shocks, such as weather shocks, are potentially important determinants of price dynamics. Spatial and temporal arbitrages are expected to smoothen the effects of weather shocks on prices by stabilizing the supply of agricultural commodities and also calming down exuberant price expectations. However, storage may also result from hoarding behavior, especially in less developed markets, in which case, storage may actually play a destabilizing role on prices (von Braun and Tadesse, 2012).

In general, factors affecting price dynamics can be classified into short- and long-term. Long-term factors include income levels, changes in tastes and preferences, technological change, population growth, and other similar trend-setting variables. Short-term factors are idiosyncratic shocks around the long-term trend. Extreme weather events are a major example of these idiosyncratic shocks. The extent by which short-term idiosyncratic shocks affect agricultural commodity prices depends on the institutional setting made up of national policies on trade, exchange rate, market structure, net food trading position of the country, amount of commodity stocks at the time of the shock and others. Weather shocks can affect crop prices through impacting their supply and by changing people's perceptions and expectations about the future price dynamics, which is reflected through their storage decisions.

Time series can be decomposed into trend, seasonal, cyclical, and idiosyncratic components using unobserved-components method (Harvey, 1990). This decomposition method can be usefully exploited in the current analysis. Weather shocks are expected to have random distribution and their effects on agricultural prices are only short-term. Although there are studies demonstrating that the effects of weather shocks on agricultural price volatility could potentially lead to long-term effects, for example, on children's health in poor countries (Jensen, 2000), it may be safe to accept that weather shocks do not have permanent long-term effects on agricultural prices *per se*. Consequently, the effects of weather shocks on agricultural prices are fully captured by the idiosyncratic components of agricultural price series. Weather shocks themselves represent the idiosyncratic components of specific weather variables such as temperature and precipitation. Long-term factors affecting the prices such as income levels and population growth; or climate change in the case of the weather variables, are captured by the trend component of the time series. Hence, a straightforward way of assessing the effects of weather shocks on agricultural prices would be to decompose the variables in the model into their latent components, and look into only the idiosyncratic components of the variables in the regression analysis.

The analysis of weather impacts on agricultural prices using the panel data whose both cross-sectional and time dimensions are quite long (T-132 and N-38) effectively precludes from applying the conventional workhorse methods of price analysis such as VAR or VECM, but may necessitate the use of methods from the newly developing field of panel cointegration to account for potential non-stationarity aspects of very long panel data. The proposed approach is based on the idiosyncratic components of individual time series and hence the analysis is greatly simplified since the idiosyncratic components are by definition stationary and can be effectively tackled by simpler and time-proven panel regression techniques.

{The location for Figure 1}

The conceptual approach is summarized in Figure 1. All the variables are represented by their idiosyncratic components. The conceptual framework schematically represents the following functional relationships between the employed variables of interest.

$$Y = f(T, R, Ir, E, In, P_{int}, d) \quad (1)$$

$$S = f(T, R, Ir, E, In, P_{int}, d) \quad (2)$$

$$P = f(\hat{Y}, \hat{S}, E, In, P_{int}, d) \quad (3)$$

where,

Y – shocks, or deviations from trend, in wheat yields

S – shocks in commodity stocks

P – provincial prices for wheat

T- shocks in mean monthly temperature

R- shocks in monthly accumulated rainfall amounts

Ir- shocks in the availability of irrigation water

E – shocks in national exchange rate

In - province level inflation rates

d – dummies standing for other country and time-specific unobserved shocks

$\hat{Y}$, $\hat{S}$ – fitted values for yield and stock shocks from the first stage of the model

Throughout this paper, the shocks are defined as deviations from trend in the variables. For example, mean temperature in a specific month could be 2°C higher than what is otherwise expected based on the temperature trend. In the analysis this is considered as positive shock of 2°C, where the term "positive" is used in its strictly mathematical meaning, i.e. more than zero, without any normative connotations.

This approach at evaluating weather shocks as deviations from trend rather than deviations from the mean is based on the assumption that economic agents continuously update their cognitive perceptions so that their actions are shaped by changing trends in climate rather than long-term mean climate values which could become no longer relevant for their decision-making, especially in the context of accelerated climate change.

In the first stage of the analysis, the effects of shocks in temperature, precipitation and availability of irrigation water on yield and commodity stock shocks are estimated. The regression model also controls for the concurrent shocks in inflation, exchange rate, the international price for the corresponding agricultural commodity and for other unobserved time and country-specific idiosyncratic shocks that may have influence on stocking and production decisions.

Weather shocks could influence agricultural prices through two channels: i) through influencing expectations about the future prices, which gets reflected through stocking decisions, ii) through directly impacting the yields and hence the production of agricultural commodities.

The first channel, which can be called as expectations link, operates through both private and public decisions on stock holdings for the affected commodity. Both private and public agents utilize all the available information in their decision making process. In this regard, when confronted with weather shocks and their potential effects on future supply of agricultural commodities, economic agents respond to these shocks by adjusting their storage decisions. If a negative weather shock happens, for example, drier than usual weather or outright drought in the rainfed areas, private economic agents, seeking to maximize their profits, would expect a lower future harvest and thus future higher prices, which would lead them, *ceteris paribus*, to increase stocks, or at minimum, decelerate their destocking levels – which would put an upward pressure on the prices. On the other hand, the public agent's (i.e. Government) major political interest involves maintaining stable and affordable prices. Any upward movement in the prices that would be deemed excessive would result on releases from public stocks to bring the prices down. The final outcome would depend on the interaction between the private and public stockholders (Jayne and Tshirley, 2009). Due to limitations on the availability of separate data on public and private stockholdings, the current analysis could not distinguish between these two types of stockholdings, but traces only the effects of weather shocks on aggregate stock levels.

In addition to the expectation link, there is also a direct production link between weather shocks and commodity prices through the effect of weather shocks on crop yields. Higher than usual rainfall amounts in rainfed areas (positive shocks), for example, could lead to bumper harvests thus increasing the supply of agricultural commodities, and potentially leading to lower prices.

The weather variables and availability of irrigation water are entered into the regression models both in their levels and also in quadratic forms to capture potential nonlinearities. A little bit more of rain could be beneficial for crop production, but if there is too much rain it may retard field operations, may lead to occurrence of plant diseases, such as yellow rust in Central Asia, may cause floods and landslides in hilly areas, etc. A full set of interactions between temperature, precipitation and availability of irrigation water is also included in the first stage estimation to account for their joint effects. The first stage of the regression also accounts for the effects of idiosyncratic shocks in exchange rate, inflation, the international price for the commodity and other unobserved time- and country- specific shocks, since they may also have influence on the stocking and production decisions, and their omission will bias the coefficient estimates (Baltagi, 2002). For example, the Central Asian countries pursue various and numerous policies on import and export tariffs for agricultural commodities, on stabilizing domestic prices for key staple foods through stocks, production quotas, trading permits, etc – which the model does not capture explicitly, but strives to account for the effect of these factors implicitly through the inclusion of time- and country- specific dummy variables.

The second stage of the model has wheat prices as dependent variables, and looks into how the latter are impacted by the fitted values of shocks in wheat stocks and yields, shocks in the global prices for the wheat, exchange rates and inflation. For tradable commodities, such as wheat, international price fluctuations are important factors in determining the domestic prices, especially in small open economies. For this reason, the shocks in the global prices of commodities are included to capture the effect of exogenous price shocks on commodity prices inside the country. Sensitivity of internal prices to changes in global prices also shows the level of integration between domestic and international markets, as well as the extent of national barriers for price transmission such as price controls, subsidies and other kinds of government interventions. In addition to external shocks, the model also needs to account for internal macroeconomic shocks that may affect prices. Consequently, it also includes exchange rate and inflation fluctuations. The devaluation of the local currency against the US dollar decreases the local commodity prices in dollar terms if the major part of the national supply of that commodity is produced inside the country. However, devaluation would increase the prices of commodities if they are mainly imported from outside. Regarding inflation, including the current levels of the inflation directly into the model may create endogeneity problem between the dependent variable – commodity price, and inflation as the explanatory variable, as commodity prices may actually drive the inflation dynamics. This is true especially in the case of food commodities in the poor countries, where food constitutes a major portion of aggregate consumer demand. To avoid this potential endogeneity problem, the lagged values of inflation are included in the model. The relationship between stocks and commodity prices, between commodity prices and yield shocks may also be endogenous. The use of the two stage model provides with a key advantage of instrumentalizing these endogeneities by using fitted values of stocks and yield shocks conditioned on weather and other variables. Following Roberts and Schlenker (2009) the model includes the interaction of stock and yield shocks in order to capture any possible joint effects. It is expected that that larger stocks, bumper harvests and their interaction terms are negatively associated with commodity prices. The model also includes country and time dummies to account for the effect of directly unobserved country- and time-specific idiosyncratic shocks. Finally, in both stages of the estimation, the lag structure of all the explanatory variables is considered, where the selection of the number of lags is guided by Akaike Information Criterion (Akaike, 1974).

4. Econometric strategy

The empirical estimation consists of three steps. First, all variables in the model are decomposed into their idiosyncratic components. Secondly, the idiosyncratic components are tested for the presence of unit root to make sure that the series are stationary and linear panel regression methods can, thus, be used. Finally, the parameters are estimated using Feasible Generalized Least Squares (FGLS) panel regression.

To decompose variables into their latent components by separating trend, cyclical, seasonal and idiosyncratic components, the unobserved-components model (UCM) approach is applied. The general form of the UCM is written as:

$$T_t = \alpha_t + \beta_t + \phi_t + \delta X_t + \epsilon_t \qquad (4)$$

where, T_t, is the dependent variable, α_t represents the trend, β_t seasonal component, ϕ_t cyclical component, δ regression parameters for exogenous variables X_t, and ϵ_t idiosyncratic components. UCM does not have to have all these specified elements at the same time. Following Harvey

(1990), the time series data are modeled as random walk. Separate unobserved components regressions are run for each of the variables in each of the cross-sectional units, i.e. provinces, and then the idiosyncratic components of these variables are collected for further analysis.

The second step in the analysis is to test the idiosyncratic components for the presence of unit root to make sure that the series are stationary. For this purpose, the recent developments in panel unit root tests are availed of. These methods allow for better handling of the cross-sectional dependencies and serial autocorrelations obviously present in spatial distribution of weather events and regional price dynamics. In addition, the use of panel approach in testing for the unit root, as compared to separate pure time-series based unit root tests, provides with a larger number of observations, thus increasing the degrees of freedom (Erdil and Yetkiner, 2004). There are several methods of panel unit root tests. They can be broadly classified into two categories: those which account for cross-sectional dependence and those which do not. Such test as those developed by Choi (2006), Pesaran (2003), Bai and Ng (2004), Chang (2002, 2004), Moon and Perron (2004) are in the first category, and those developed by Maddala and Wu (1999); Breitung (2000), Hadri (2000), Choi (2001), Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) are in the second category (Barbieri, 2006). To be able to choose the right unit root test, the panels are first tested for cross-sectional dependence using the test developed by Pesaran (2003). After having identified the presence of cross-sectional dependence in the panels, testing for panel unit is conducted by accounting for cross-sectional dependence. Specifically, the Pesaran panel unit root test in the presence of cross-sectional dependence is applied (Pesaran, 2007)).

The final step involves estimating the model described earlier in the conceptual framework using FGLS panel regression. Econometrically, the first and second stages of the model are specified as follows (with appropriate lags):

1rst Stage:

$$Y = T + T^2 + R + R^2 + Ir + Ir^2 + T{**}R{**}Ir + T^2{**}R^2{**}Ir^2 + E + In + P_{int} + d \qquad (5)$$

$$S = T + T^2 + R + R^2 + Ir + Ir^2 + T{**}R{**}Ir + T^2{**}R^2{**}Ir^2 + E + In + P_{int} + d \qquad (6)$$

2nd Stage:

$$P = E + In + P_{int} + \hat{Y} + \hat{S} + \hat{Y}^2 + \hat{S}^2 + \hat{Y}*\hat{S} + \hat{Y}^2*\hat{S}^2 + \quad d \qquad (7)$$

where,

Y – shocks, or deviations from trend, in wheat yields, S – shocks in wheat stocks, P – provincial prices for wheat, T- shocks in mean monthly temperature, R- shocks in monthly accumulated rainfall amounts, Ir- shocks in the availability of irrigation water, E – shocks in national exchange rate, In - province level inflation rates, d – dummies standing for other country and time-specific unobserved shocks, $\hat{Y}$, $\hat{S}$ – fitted values for yield and stock shocks from the first stage of the model.

The choice of the FGLS panel regression method is based on its several advantages. As we shall see further, decomposition of the variables into their idiosyncratic components, in addition to being theoretically sensible approach in this context, also resolves the issue of non-stationarity in the variables, since idiosyncratic shocks are expected to be stationary. However, there still remain several problems in the data series for which the estimation approach employed should account for. These problems are dependence in the cross-sectional units, autocorrelation and heteroscedasticity. Feasible generalized least squares approach is the technique that is capable of adequately handling all these remaining problems, which motivates the choice of the technique for the empirical estimation.

5. Data

The dataset used consists of monthly panel variables for the 38 provinces in Central Asia for the period of 10 years between 2000 and 2010 as described in detail in Table 1.

{The location for Table 1}

Although this dataset is the first such a relatively rich and detailed long-term monthly dataset available for Central Asian countries, it has limitations and contains gaps, primarily in the stock and price variables. Therefore, in cases of provinces where there were missing points in any of these variable series, the missing data were imputed using the fitted values from the OLS regressions involving the variables for the neighboring provinces for which these data were available. There were fewer gaps in the available price series for the provinces of Kazakhstan, Tajikistan and Kyrgyzstan, while more gaps were in the price data for the provinces of Uzbekistan. The major underlying assumption behind the applied imputation method for missing data is the existence of strong price co-movement between the neighboring provinces. This seems to be a valid assumption, especially in the case of Uzbekistan where differences in agricultural prices within the provinces inside the country are small (Grafe, Raiser, and Sakatsume, 2005). This assumption is also corroborated by our own analysis of a separate dataset of retail prices for major 24 agricultural commodities between 2009 and 2010 in Uzbekistan. The average provincial cross-correlations in retail prices for these 24 agricultural commodities range between 0.81-0.98, and are reported in Table 2.

{The location for Table 2}

Moreover, there is some evidence that the level of integration in agricultural consumer prices among the countries of Central Asia is also high (ibid.). As with most available cereal stock data (Wiggins and Keats, 2010), there may be unknown measurement errors in the stock variables, especially in terms of accurately estimating the extent of private stocks in the country. Importantly, the available data, unfortunately, does not allow for separating private and public stocks in order to econometrically account for differing aspects in the behavior of public and private stockholders, thus constituting a limitation of this study. In spite of all these actual and potential data limitations, it is believed that the results presented below can adequately serve as first, even if rough, estimates of the effects of specific temperature, precipitation and irrigation water availability shocks on agricultural prices, in the example of Central Asia. Crucially, the suggested new estimation method could be fruitfully used in future work involving less constraining datasets.

6. Results and Discussion

Following the first step of the empirical approach, the time series are decomposed into their latent components. Figure 2 shows an instance of this decomposition in the example of wheat prices in Akmola province of Kazakhstan. All other variables for the remaining provinces in Central Asia are also similarly decomposed. Following this preparatory stage, the idiosyncratic components of the variables are tested for cross-sectional dependence (Table 3).

{The location for Figure 2}

{The location for Table 3}

The Pesaran test (Pesaran, 2003) strongly rejects cross-sectional independence for all variables (Table 3), with p-values significant at less than 1%. The higher is the test statistic (CD-statistic), more strongly the panels are correlated. Similarly, the columns "corr" and "abs (corr)" show the estimated strength of the cross-sectional correlation. The test has shown that idiosyncratic shocks in the variables are correlated across the countries of Central Asia. Further, for checking the presence of unit root the Pesaran panel unit root test in presence of cross sectional dependence is employed (Pesaran, 2007). The test confirms that the idiosyncratic parts of the variables are stationary (Table 4).

{The location for Table 4}

The important references to look in the table are the p-values. Selection of the right number of lags can be crucial for the unit root tests. The stationarity tests were run with up to 12 lags and in all cases the presence of unit root was rejected at less than 1%. In Table 4, the results of the unit root test based on two lags are presented. The tests confirm the theoretical hypothesis that idiosyncratic components of the variables are stationary. Thus, although non-stationarity is no longer a problem, there can be still other issues related with cross-sectional dependence, serial correlation and heteroscedasticity. The Pesaran test for cross-sectional dependence carried out earlier has also confirmed the presence of cross-sectional correlation in the dataset. Moreover, Wooldridge test for autocorrelation in panel data (Wooldridge, 2002) and Likelihood ratio test for heteroscedasticity after FGLS confirm the presence of autocorrelation and heteroscedasticity both at the first and second stages of the estimation. Based on these characteristics of the dataset, the feasible generalized least squares (FGLS) is adopted as the estimation method.

The first stage regression results using FGLS are presented in Table 5. They indicate that weather variables and availability of irrigation water may play a statistically significant role in storage decisions and yield shocks. Shocks in temperature, precipitation and irrigation seem to have a convex relationship with shocks in wheat stocks. Higher than usual temperature and precipitation amounts, better than usual water availability could lead to expectations of higher wheat yields and lower future wheat price and thus provide incentives for lowering wheat stocks.

{The location for Table 5}

This is also confirmed by statistically significant positive association between positive shocks in wheat yields (i.e., higher than usual wheat yields) and higher temperatures, precipitation and water availability. On the same token, lower water availability could encourage aggressive stock accumulation against expected supply shortfalls. Several interactions of temperature, precipitation and irrigation water availability are also statistically significant; however, mostly they are somewhat ambiguous. For example, the interactions generally have convex relationship with yield shocks when two variables such as temperature and precipitation, temperature and irrigation, and precipitation and irrigation are interacted. However, the relationship is concave when all three are interacted. In general, signs of the interactions in nonlinear models are strongly influenced by the nonlinearities in the model and should be taken with caution (Ai and Norton, 2003). Shocks in international wheat prices did not have a statistically significant effect on stock dynamics, however, they are positively associated with yield shocks, signifying that wheat producers may be responding to the changes in the international prices by modifying their production decisions, for example by applying more fertilizers when the prices go up. Kazakhstan is the only Central Asian country which may be considered as non-small supplier of wheat to the international market. Even allowing for this, the endogeneity between regional wheat yield shocks and international prices is unlikely to be a problem since under endogenous relationship the association between regional yield shocks and international prices should be negative and not positive as in the regression model. The exchange rate's impact on wheat stocks is ambiguous since the signs of the coefficients change with lags; however, it seems shocks in exchange rate seem to be positively correlated with yield shocks. Structurally, the link between exchange rate shocks and yield shocks passes through expected prices for exported output and changing prices for imported inputs, such as fertilizers and other chemicals.

We then harvested the fitted values of shocks in stocks and yields for wheat, which allows for instrumentalizing against potential endogeneity between wheat stocks and prices, yield shocks and prices, and also trace the link with weather variables. Following this, the wheat prices are regressed on these fitted values, shocks in international prices for these commodities, in exchange and inflation rates. Country and time-specific effects are also included to account for unobserved shocks during the period. The results of the second stage are given in Table 6.

{The location for Table 6}

The results indicate that wheat markets, as a whole, in Central Asia are affected by shocks in the international wheat prices. There is about 0.11 USD of contemporaneous price transmission to local prices for every 1 USD of price shock in the international wheat prices. Similarly, lagged price transmission is also statistically significant with 0.08 USD for every 1 USD price increase for wheat in the preceding month. The effect of inflation on prices is positively signed on both level and lag. Exchange rate devaluation is negatively associated with local wheat prices, both in current and lagged forms. Upward shocks in exchange rates make current local wheat prices denominated in local currency cheaper in USD terms. Wheat export and import are strongly regulated and usually conducted by the Governments themselves in Central Asia through their specialized agencies. Inputs for wheat production to some extent are subsidized in virtually all countries of the region. Shocks in stock levels and wheat yields have statistically significant effects on wheat prices. The current and lagged positive shocks in wheat stocks and crop yields lead to price decreases. The effect of positive shocks in wheat stocks and wheat yields on wheat prices is convex, as the squared terms are also statistically significant and are positively signed. The interactions of yield and stocks shocks are significant, however, the signs of interactions are opposite to the signs of individual variables, but similar to the signs of their quadratic terms, implying that interaction of stock and yield shocks moderates any dynamic effects of the individual variables on the prices. Thus, combining the two stages of the model, positive shocks in irrigation water, temperature and precipitation, i.e. warmer temperatures, more rainfall and irrigation water availability seem more likely to lead to lower wheat prices.

{The location for Figure 3}

We then look at the elasticities of changes in wheat prices with regard to changes in weather variables only. These elasticities, namely with regard to temperature, precipitation and availability of irrigation water, are striking (Figures 3). If the impact of higher temperatures on wheat prices is small and somewhat ambiguous with confidence intervals diverging at 0, the impact of lower precipitation and reduction in the availability of irrigation water are clear and, in fact, quite big. For example, reduction in precipitation by 100 mm may increase wheat prices by 64 to 318 USD per ton in the region. Similarly, a 30% reduction in the availability of irrigation water may lead to dramatic price hikes, ranging from 364 to 1650 USD per ton, all other things being equal. The availability of irrigation water seems to have the biggest potential impact on wheat prices. The magnitudes of changes simulated in Figure 3 encompass the full range of potential negative climatic changes predicted by various global circulation models for Central Asia. The highest elasticity is shown by changes in the availability of irrigation water, implying that any sizable reductions in irrigation water could lead to dramatic increases in wheat price in the region.

7. Conclusions and Implications

Weather volatility and fluctuations in the availability of irrigation water have statistically significant effects on wheat prices in Central Asia. Negative shocks in irrigation water availability and precipitation could create conditions for higher wheat prices. Lower availability of irrigation water could encourage irrigation-dependent countries of the region to raise wheat stocks to face expected supply shortfalls thus leading to higher prices. This effect could be further aggravated by negative effects of lower water availability on wheat yields. Moreover, the results show that wheat prices in the region are very sensitive to the availability of irrigation water, implying that hydrologic drought years have a strong potential to cause wheat prices spikes in the region. In order to counteract such developments, it is necessary to maintain storage policies and open trade arrangements in agricultural commodities in the region to minimize price volatility resulting from drought shocks.

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Figures

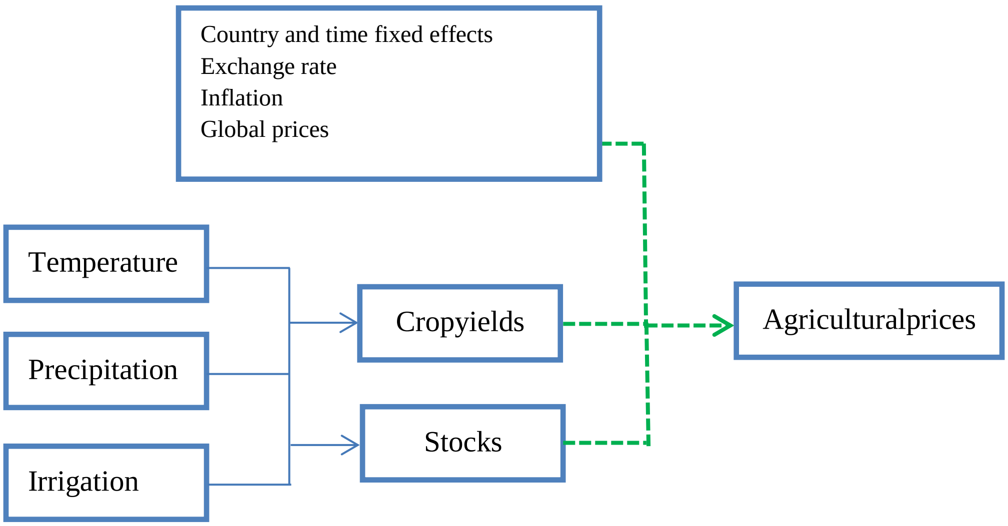

Figure 1.The conceptual framework of effects of weather shocks on agricultural prices

Note: The first stage of the regression is depicted with connected lines, while the second stage with dashed lines.

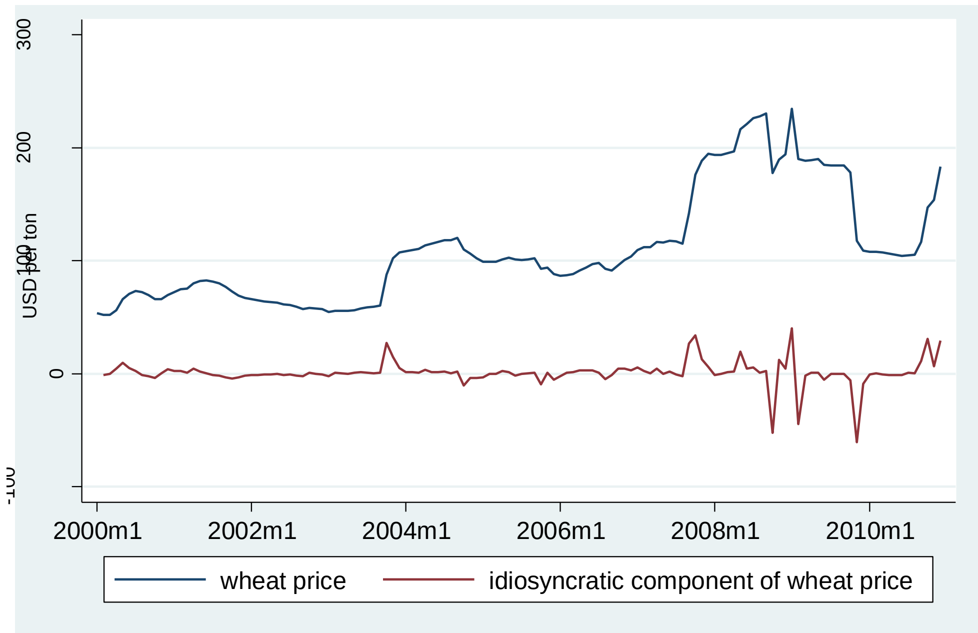

Figure 2. Decomposition of wheat price series into idiosyncratic components, Akmola province, Kazakhstan

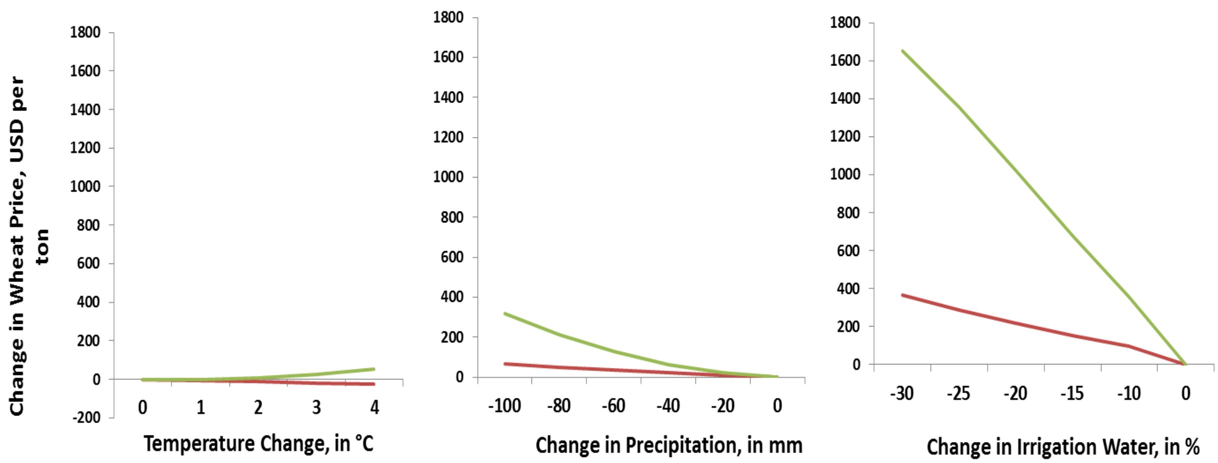

Figure 3. Comparison of the impacts of changes in temperature, precipitation and availability of irrigation water on changes in wheat prices

Note: Two lines represent higher and lower confidence intervals. Calculated based on the current lags.

Tables

Table 1. Information on the variables used in the analysis

Variables	Sources	Notes
Wheat prices	National Statistical Committees, local non-governmental organizations, price sections of various local newspapers, as well as the international databases such as FAO´s Global Information and Early Warning System (GIEWS).	Converted to US Dollar using the average exchange rate for the corresponding month
Global wheat prices	Index Mundi online database (www.indexmundi.com). Original source: United States Department of Agriculture (USDA) Market News	Wheat, No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico, in USD Dollars per metric ton
Exchange rates	National central banks as well as international online databases	National level exchange rates were assumed to be the same for all provinces within the country

Variables	Sources	Notes
	such as www.oanda.com	
Inflation rates	National central banks, national statistics agencies	Province-specific Consumer Price Index (CPI) was used. Whenever province-level CIP was not available, national CPI was used.
Weather variables	Williams and Konovalov (2008), NASA´s Global Summary of the Day, national hydro-meteorological services and other online sources such as www.rp5.uz and its sister websites for each country of Central Asia	Monthly mean temperature and total accumulated monthly rainfall. From about 400 weather stations across Central Asia. Mean monthly temperature and total monthly rainfall data from individual weather stations were spatially projected to the digital map of Central Asia using spatial interpolation technique of inverse weighted distance. Following this, the pixel-level weather variables were averaged for each province. However, before the spatial interpolation, all the weather stations located at 1000 meters above the sea level were removed from the dataset to avoid potential bias in the analysis that may be caused by high-altitude weather stations located in areas with little or no agricultural production and population settlement. However, in cases where the entire region is located in high mountain altitude areas, specifically the Gordo-Badahshan Autonomous province of Tajikistan, all the weather stations were kept.
Monthly amount of available irrigation water	Scientific-Information Center of the Interstate Coordination Water Commission of the Central Asia (SIC ICWC) available at http://www.cawater-info.net and the reports of national water management authorities	For some provinces of Kazakhstan with overwhelmingly rainfed agriculture, there were data only on annual amounts of irrigation water applied. These annual amounts were disaggregated into monthly using within month distribution of available irrigation water in the neighboring provinces for the corresponding year.
Wheat stocks	National statistical agencies as well as international databases, such as FAOSTAT	The data on stocks was not always available in monthly frequencies at provincial level. In some cases it was available only at national level on annual basis. To correct for this discrepancy, the annual data disaggregated into monthly

Variables	Sources	Notes
		frequencies using the intra-monthly distribution of stocks from the other years when monthly data were available or from neighboring countries with similar cropping calendar, farming systems, and net trading position, and the share of the province in the production of wheat was used as the weight to calculate the provincial share of the stocks.
Yield shocks	National statistical agencies	The annual wheat yield series were decomposed into their idiosyncratic components. The corresponding values of these annual idiosyncratic shocks in crop yields were assigned to all the months of the same cropping year. In applying this procedure, it was assumed that crop yields at the point of harvest are influenced by all previous events that have taken place throughout the immediate cropping year.

Table 2. Average cross-correlations of major 24 agricultural commodities among the provinces of Uzbekistan between January, 2009 and January, 2010*.

Provinces	Kar	And	Buh	Jiz	Qash	Nav	Nam	Sam	Sur	Sir	Tosh	Far	Hor
Karakalpakstan	1.00												
Andijon	0.88	1.00											
Buhoro	0.88	0.95	1.00										
Jizzah	0.83	0.92	0.89	1.00									
Qashkadaryo	0.84	0.96	0.96	0.88	1.00								
Navoi	0.91	0.96	0.95	0.86	0.96	1.00							
Namangan	0.86	0.98	0.96	0.91	0.95	0.93	1.00						
Samarqand	0.83	0.95	0.96	0.92	0.98	0.93	0.95	1.00					
Surhandaryo	0.83	0.95	0.97	0.90	0.97	0.93	0.95	0.97	1.00				
Sirdaryo	0.83	0.98	0.95	0.92	0.96	0.94	0.98	0.97	0.97	1.00			
Toshkent	0.81	0.96	0.95	0.92	0.96	0.92	0.97	0.97	0.96	0.98	1.00		
Farg'ona	0.87	0.98	0.96	0.93	0.97	0.95	0.98	0.97	0.97	0.98	0.97	1.00	
Horazm	0.88	0.93	0.96	0.94	0.93	0.93	0.94	0.95	0.96	0.94	0.94	0.96	1.00

* The names of the provinces are abbreviated in the top row to fit the table into the page. The sequence of the provinces in the top row is the same is in the leftmost column.

Table 3.Pesaran test for cross-sectional dependence

Variable	CD-statistic	p-value	corr	abs(corr)
Wheat price	77.61	0.000	0.255	0.349
Precipitation	76.34	0.000	0.251	0.268
Temperature	168.99	0.000	0.555	0.555
Irrigation water	99.23	0.000	0.326	0.343
Wheat stocks	172.09	0.000	0.565	0.567
Inflation rate	117.53	0.000	0.386	0.386
Exchange rate	118.11	0.000	0.388	0.388

Table 4. Pesaran panel unit root test in presence of cross sectional dependence

Variables	t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
Wheat price	-6.0	-2.1	-2.1	-2.2	-28.5	0.000
Precipitation	-5.9	-2.1	-2.1	-2.2	-27.6	0.000
Temperature	-5.2	-2.1	-2.1	-2.2	-23.2	0.000
Irrigation water	-6.2	-2.1	-2.1	-2.2	-29.8	0.000
Wheat stocks	-6.1	-2.1	-2.1	-2.2	-29.4	0.000
Inflation rate	-6.2	-2.1	-2.1	-2.2	-29.8	0.000
Exchange rate	-5.1	-2.1	-2.1	-2.2	-22.3	0.000

Note: 2 lags.

Table 5. First stage of the model: impact of weather and other variables on yields and stocks (* p<0.01, ** p<0.05, * p<0.1)**

VARIABLES	Wheat yield	Wheat stocks (log)
International price for the commodity		
Level	0.000121**	0.000665
Lag 1	4.71E-05	0.000396
Lag 2	0.000110**	-0.000524
Inflation		
Level	-4.05E-05	0.00777***
Lag 1	-0.000168	0.00321
Lag 2	0.000272	0.000756
Exchange rate		
Level	0.000894***	-0.00320*
Lag 1	0.000602***	0.00504**
Lag 2	0.000447**	-0.00177
Temperature		
Level	0.0219***	0.00929
Lag 1	0.0111***	-0.0113
Lag 2	0.00195	-0.0529***
Precipitation		
Level	0.00157***	0.00315*
Lag 1	0.000351	-0.00148
Lag 2	-0.00043	-0.00594***
Irrigation (log)		
Level	0.0231***	0.0206
Lag 1	0.0122***	-0.0141
Lag 2	0.00317	-0.0357**
Temperature, squared		
Level	0.000372***	0.00296***
Lag 1	5.14E-05	0.000693***
Lag 2	-1.13E-05	0.000470**
Precipitation, squared		
Level	-7.28E-07	1.42E-06
Lag 1	-9.29E-07	1.20E-06
Lag 2	-8.59E-07	2.52E-06
Irrigation (log), squared		
Level	0.000170***	0.000741**
Lag 1	0.000212***	0.000650**
Lag 2	0.000251***	-0.000471
Interactions		
Temperature and precipitation		
Level	-0.000138***	-3.44E-05
Lag 1	-1.69E-05	0.000172
Lag 2	4.16E-05	0.000641***
Irrigation and temperature		

VARIABLES	Wheat yield	Wheat stocks (log)
Level	-0.00313***	-0.000654
Lag 1	-0.00189***	0.0015
Lag 2	-0.000711**	0.00470***
Irrigation and precipitation		
Level	-0.00023***	-0.000345**
Lag 1	-0.00013***	7.71E-05
Lag 2	-4.88E-05	0.000384**
Temperature, precipitation and irrigation		
Level	2.17e-05***	2.64e-05*
Lag 1	1.14e-05***	-6.66E-06
Lag 2	3.96E-06	-4.67e-05***
Temperature and precipitation, squared		
Level	-3.12e-08***	-1.09e-07***
Lag 1	-2.89e-08***	-4.07e-08**
Lag 2	-1.96e-08***	-3.63e-08**
Irrigation and temperature, squared		
Level	3.00e-06***	-5.88e-06***
Lag 1	2.09e-06***	-3.45e-06***
Lag 2	8.66e-07***	-2.21e-06**
Irrigation and precipitation, squared		
Level	3.28e-08***	4.86E-09
Lag 1	3.16e-08***	2.44E-08
Lag 2	2.71e-08***	4.99e-08**
Temperature, precipitation and irrigation,		
Level	-6.93e-11***	0
Lag 1	-6.20e-11***	-5.34E-11
Lag 2	-5.41e-11***	-7.69e-11*
Country and time- effects	**yes**	**yes**
Constant	**0.698*** **	**-0.912**
Observations	**4,940**	**4,940**
Number of panel	**38**	**38**

Table 6. Second stage of the model: impact of shocks in stocks in yields and other variables on shocks in provincial wheat prices

VARIABLES		Wheat price
International prices for the commodity (USD/t)		
	Level	0.11***
	Lag 1	0.08***
Inflation		
	Level	0.1
	Lag 1	0.65***
	Level	-3.8***
	Lag 1	-1.8***
Yields (t/ha)		
	Level	-249***
	Lag 1	-389***
Stocks (log)		
	Level	-48***
	Lag 1	-63***
Interaction of stock and yield shocks		
	Level	572*
	Lag 1	2074***
Yield shocks, squared		
	Level	2,870***
	Lag 1	915
Stock shocks, squared		
	Level	131***
	Lag 1	-27
Interaction of stock and yield shocks, squared		
	Level	-1,264
	Lag 1	-21,472***
Country and time effects		yes
Constant		-33,1***
Observations		4,902
Number of panel		38

*** p<0.01, ** p<0.05, * p<0.1