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Comment Derek Headey

Overview of the Chapter

In this chapter Berry, Roberts, and Schlenker extend some of their earlier work on the effects of weather shocks on US maize production. A key motivation for their chapter—and the link to the broader theme of this book—is that the United States is a major producer and exporter of maize, such that production shocks in the United States are a potential driver of maize price volatility, which may have important ramifications for the world's poor.[1] The main technical innovations of this chapter are that they now allow the effect of various weather measures to evolve over the growing season, and that the growing season is made more location specific. This new and improved model is then applied to the 2012 growing season, when large parts of the US maize belt experienced a severe heat wave and drought. Strikingly, their improved model predicts yield declines of up to 24 percent. In their concluding remarks they note that some climate change models predict that these kinds of heat spells/droughts may well be the new normal in the US maize belt.

My comments will be confined to four areas: a few technical issues, a quick look at whether their predictions came true, some discussion and exploratory analysis of the impact of US maize production on international prices, and some policy and programmatic implications of their model and results.

Some Technical Issues

Technically, the chapter is strong. The authors build on much simpler attempts to model weather with production outcomes, with a particular

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1. Maize is the most important staple food in Africa, and a major crop in Latin America.

focus on hot days, defined as those exceeding 29 degrees Celsius. Nevertheless, I have a few concerns with the empirics of the chapter.

First, while the authors do show that the explanatory variables of the model have highly significant marginal effects, there is not much discussion of goodness of fit or predictive capacity of the model. But an obvious use of this kind of model—and one which I discuss below—is that it might serve as an early warning device, or as a gauge of the likely impact of climate change.

Second, the authors refer to the agronomic literature without ever actually citing it. More details would be welcome, particularly those related to heat stress, and particularly given that they make a point of noting that their model looks largely consistent with agronomic evidence. Such evidence should be cited.

Third, on a related note, while the authors engage in quite a few sensitivity analyses, they never vary the 29 degree Celsius threshold. Perhaps they, or others, have done so in earlier work, but the use of a threshold always makes readers wonder whether the choice of threshold is robust.

Fourth, while the authors attempt to model interactions between heat days and precipitation, they do not find any significant interactions. It seems rather unintuitive that heat and moisture (broadly defined, rather than just precipitation) would not interact in some way. One would not expect heat in excess of 29 degrees in very cloudy and humid conditions to have the same effects as very dry heat, particularly prolonged dry heat. Clearly, weather is a highly nonlinear phenomenon in terms of the existence of thresholds and likely interaction effects. However, modeling these nonlinearities—particularly interaction effects—is always very challenging. In this case they interact hot days with precipitation, but precipitation itself seems to have a quadratic relationship with production, which potentially presents an additional challenge to finding a significant interaction effect between precipitation and hot days. While the authors make a sensible attempt to find such a significant interaction, I would urge them to keep testing and experimenting with different specifications and methods.

Predictive Capabilities of the Model

Turning to my second set of comments, the data in this study extend up to August 31, 2012. As such, the authors have a good set of data to make predictions about the summer harvest of 2012, although writing in May of 2013 I now have access to the United States Department of Agriculture (USDA)'s estimates of actual maize production in 2012, which I report in table 2C.1. Specifically, I report yields, production and area, as well as stocks and exports as a share of production. The key number in table 2C.1 is the –16.2 percent drop in maize yields in 2012. This falls in the range of estimates presented by Berry et al. (–15 to –24 percent), but is toward the lower end of that range, particularly the number derived by their unimproved base-

Table 2C.1 **Did their predictions come true? Trends in the US maize sector, 2010–2013**

	Yields (tons)	Production (1000s mt)	Area (1000s ha)	Stocks (% of production)	Exports (% of production)
Levels					
2010	9.59	316,165	32,960	32.4	14.3
2011	9.24	313,949	33,989	31.7	12.2
2012	7.74	273,832	35,360	39.1	7.1
2013[a]	9.92	359,173	36,220	29.6	9.2
Year-on-year growth rates					
2011	–3.7%	–0.7%	3.1%	–2.4	–14.5
2012	–16.2%	–12.8%	4.0%	23.4	–41.8
2013[a]	28.1%	31.2%	2.4%	–24.4	29.0

Source: USDA (2013).

[a]2013 numbers are presumably USDA projections, since the data were downloaded in May 2013.

line model (–15 percent). Nevertheless, the discrepancy between this –16.2 percent estimate and the –24 percent estimate of their most favored model could be explained by different spatial coverage (Berry et al.'s sample pertains to those counties east of the 100 degree meridian, rather than the whole country), and even by some measurement error in the USDA numbers. On the whole, though, their modeling approach shows substantial predictive capacity for 2012. Nevertheless, it would be useful for the authors to retrospectively revisit the predict capacity of their model for the 2012 season after updating their data set. The authors could then explore ways of tweaking the model to improve their predictions, including my suggestion for more extensive testing of nonlinear specifications.

The Links between Climatic Shocks and Food Price Volatility

One weakness of the chapter, albeit from a purely thematic standpoint, is that the authors do not empirically link their analysis to food price volatility. Obviously, the impact of weather shocks on food price volatility is a key motivation for their chapter. The authors note, for example, that the United States accounts for around 40 percent of global maize production, for example. They might also note that the United States accounts for between 50 to 60 percent of global trade (depending on the year), suggesting that the impact of US policies, macroeconomic shocks, and weather shocks might be as large—if not larger—than the impact of policies in the entire rest of the world! Many discussions of the 2008 food price spike also viewed weather shocks as a significant factor, particularly as these shocks acted as a catalyst for trade restrictions and precautionary imports, which further exacerbated price volatility (Dollive 2008; Headey 2010; Headey and Fan 2010).

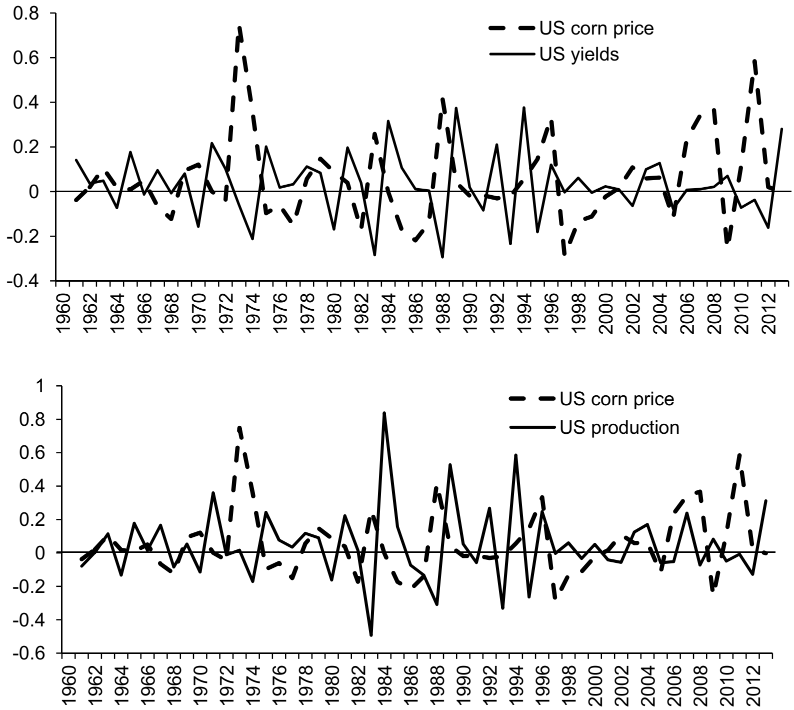

Fig. 2C.1 US production and yield shocks and maize prices
Source: USDA (2013).

But while the links between weather shocks in the United States and global food prices seem intuitive, the issue is not straightforward, particularly because of the potentially dampening effects of grain stocks/reserves. Even if weather shocks become more frequent and severe in the future, food price volatility could well be mitigated by more prudential stocking policies.[2]

Since the 2008 crisis a large number of econometric studies have emerged that try to explain food price dynamics, but I cannot recall a specific paper looking at the impacts of US production shocks on food price dynamics. I have little scope to delve into the issue in any detail here, but in figure 2C.1 and table 2C.2 I take a preliminary look at the relationship between these variables. Figure 2C.1 shows the relationship between maize prices and maize yields in the top panel, and maize prices and maize production in the bottom panel. Yields are presumably strongly driven by weather events in the US context of relatively stable farm policies, but production is partly a

2. At the same time, one issue in the analysis of the 2008 crisis was that low stocks were arguably overemphasized, since weather shocks and strong demand actually drove down private stocks. So to some extent low stocks were a symptom of the crisis, rather than a cause.

Table 2C.2 VAR regressions linking prices, production, stocks, exports for the United States (-A) and the rest of the world (-W)

Prices equation			Production-A equation			Stocks-W equation			Exports-W equation		
	Lag	Elasticity		Lag	Elasticity		Lag	Elasticity		Lag	Elasticity
Prices	L1.	0.10	Prices	L1.	–0.30	Prices	L1.	0.15	Prices	L1.	0.20
	L2.	–0.14		L2.	0.13		L2.	0.00		L2.	–0.32
Stocks-A	L1.	–0.27***	Stocks-A	L1.	–0.21**	Stocks-A	L1.	–0.09[a]	Stocks-A	L1.	–0.13
	L2.	0.09		L2.	–0.11		L2.	0.08		L2.	–0.10
Production-A	L1.	0.38*	Production-A	L1.	–0.47*	Production-A	L1.	0.18	Production-A	L1.	0.32
	L2.	0.13		L2.	–0.11		L2.	0.06		L2.	0.17
Exports-A	L1.	0.21	Exports-A	L1.	0.05	Exports-A	L1.	0.06	Exports-A	L1.	–0.21
	L2.	0.22[a]		L2.	0.16		L2.	0.10		L2.	–0.02
Stocks-W	L1.	0.16	Stocks-W	L1.	0.07	Stocks-W	L1.	0.56***	Stocks-W	L1.	–0.34
	L2.	–0.49*		L2.	0.11		L2.	–0.28[a]		L2.	0.30
Production-W	L1.	–0.66	Production-W	L1.	0.94	Production-W	L1.	–1.13**	Production-W	L1.	1.56
	L2.	0.72		L2.	0.14		L2.	0.25		L2.	0.73
Exports-W	L1.	–0.02	Exports-W	L1.	0.19	Exports-W	L1.	–0.09	Exports-W	L1.	–0.51**
	L2.	0.09		L2.	0.30		L2.	0.03		L2.	–0.30

(*continued*)

Table 2C.2 (continued)

Prices equation			Production-A equation			Stocks-W equation			Exports-W equation		
	Lag	Elasticity		Lag	Elasticity		Lag	Elasticity		Lag	Elasticity
Prices	L1.	–0.32	Prices	L1.	–0.63**	Prices	L1.	0.04	Equation	rmse	*R*-sq
	L2.	0.31		L2.	0.30		L2.	0.02			
Stocks-A	L1.	–0.51**	Stocks-A	L1.	0.18[a]	Stocks-A	L1.	–0.05**	Prices	0.14	0.54
	L2.	0.22		L2.	–0.07		L2.	–0.01	Stocks-A	0.43	0.45
Production-A	L1.	0.68	Production-A	L1.	–0.94***	Production-A	L1.	0.08	Production-A	0.17	0.55
	L2.	–0.40		L2.	0.01		L2.	0.12**	Exports-A	0.22	0.40
Exports-A	L1.	–0.65	Exports-A	L1.	0.08	Exports-A	L1.	0.04	Stocks-W	0.10	0.43
	L2.	0.33		L2.	0.34[a]		L2.	0.01	Production-W	0.04	0.64
Stocks-W	L1.	0.08	Stocks-W	L1.	0.31	Stocks-W	L1.	0.07	Exports-W	0.23	0.37
	L2.	0.54		L2.	–0.13		L2.	–0.20***			
Production-W	L1.	3.46*	Production-W	L1.	–0.03	Production-W	L1.	–0.67***			
	L2.	0.34		L2.	–0.05		L2.	0.13			
Exports-W	L1.	0.44	Exports-W	L1.	0.00	Exports-W	L1.	–0.05			
	L2.	0.52		L2.	0.27		L2.	0.04			

Sources: All data, except prices, are derived from USDA (2013). Prices are from FAO (2013).

Notes: Regressions are VAR with seven equations, two lag lengths, with all variables specified as the log of first differences. Regressions used annual data covering the years 1963 to 2013.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

[a]Denotes marginal insignificance at the 10 percent level.

function of planting decisions, which are endogenous with respect to prices. When eyeballing the data, one can certainly see some instances in which both production and yields move in opposite directions, and in which a yield/production shock precedes or coincides with a price shock: 1983, 1988, 1995 are strong instances and pertain to price spikes mentioned in the literature. However, if anything, the relationship breaks down after 1995. For example, for yields the correlation with maize prices is –0.35 prior to 1996, but just –0.05 afterward. For production, the correlation is –0.18 prior to 1996 and +0.10 afterward. From this we can infer that many other factors have been driving food prices in recent times. Indeed, even the tremendous 16 percent drop in yields in 2012 does not appear to have had any sizeable impact on international prices.

In table 2C.2 I conduct a very preliminary and exploratory vector autoregression (VAR) analysis of some of these relationships for both US production (denoted –A) and rest of the world production (denoted –W). Specifically, I examine the differences of the log of prices, production, stocks, and exports for both the United States and the rest of the world, implying a VAR system with seven endogenous variables. I make no pretensions that this analysis is sufficiently rigorous to draw strong inferences, since caveats abound: data quality for the rest of the world are pretty questionable, and I have made no theoretical attempt to address the complex role of stocks and little effort to empirically test other specification issues such as structural breaks, interaction effects, threshold effects, and so on (with one exception noted below). Also note that I use US production shocks rather than yield shocks, since it is presumably production that is the direct determinant of a supply shock, rather than yields (even so, the correlation between the two is a very high 0.90). The VAR approach has the advantage of treating all these variables as endogenous, but it could also be criticized as being quite atheoretical. I therefore limit my inferences to highlighting some apparent stylized facts that warrant a more rigorous analysis in the future.

With these caveats in mind, what does table 2C.2 suggest about the role of US production and stocking behavior in determining food prices? In the top left quadrant we see that changes in prices are indeed significantly associated with the first lag of production, with a reasonably large (but moderately significant) elasticity of 0.38. However, we also observe that the first lag of US stocks and the second lag of world stocks are significant, with respective elasticities of –0.27 (significant at the 1 percent level) and –0.49 (significant at the 10 percent level). As expected, this points to a potentially causal effect of stock changes on prices. One might also expect important interaction effects: production shocks may not matter much if existing stocks are high. I find some evidence of that through an ordinary least squares (OLS) regression (with two AR terms not reported), which interacts the lagged change in production with the lagged stocks-to-use ratio for the United States:

$$\Delta \ln \text{price} = -0.39 * \Delta \ln \text{prod}_{t-1} + 0.01 * \Delta \ln \text{prod}_{t-1} * \text{stocks}_{t-1}.$$

The regression suggests that the impact of a –10 percent production shock will result in a 0.9 percent price increase when stocks are high (e.g., 30 percent of use), but a 2.9 percent price increase when stocks are low (e.g., 10 percent of use). Again, there are plenty of caveats in a regression such as this, but the finding is nevertheless intuitive.

Another finding of potential importance pertains to the price impacts of US exports. In table 2C.2 the first and second lags of US exports are reasonably large (0.21 and 0.22) but not quite significant at the 10 percent level. However, more parsimonious specifications that drop the mostly insignificant rest of the world variables suggest that the first lag of US exports has an elasticity of 0.22 that *is* significant at the 10 percent level.[3] US exports represents foreign demand for US maize, which previous studies have shown to be quite volatile and highly correlated with international prices (Headey 2010).

There are some other findings of potential significance in table 2C.2: (a) lagged US stocks negatively affect US production (presumably through planting decisions); (b) increases in US production and prices reduce exports to the rest of the world; and (c) several of the rest of the world results mirror the result for US production, stocking, and trade relationships.

In summary, table 2C.2, and the additional regressions referred to above, suggest that:

1. US production shocks do have a reasonably strong impact on US prices (which are conventionally taken as international prices);
2. the effect of production shocks is conditioned by US stock levels; and
3. foreign demand may well be another important factor in explaining price dynamics.

Policy Implications

The linkage between US production shocks and world prices does indeed provide an important motivation for developing econometric models that can successfully predict US production shocks. One can imagine that the model developed by Berry et al. (or future variants thereof) might therefore be very useful for at least three areas of application.

Short-Term "Early Warning" Models

Currently the USDA and similar institutions around the world do give weather forecasts in the hope of improving production and stocking decisions, and in some cases such institutions also give yield and production

3. Specifically, that model for US variables only yields the following results in the prices equation: $\Delta \ln \text{price} = -0.26 * \Delta \ln \text{stocks}_{t-1} + 0.39 * \Delta \ln \text{prod}_{t-1} + 0.22 * \Delta \ln \text{exports}_{t-1}$.
The first coefficient is significant at the 1 percent level and the last two coefficients are significant at the 10 percent level.

forecasts (presumably based on models bearing some similarity to those in Berry et al.). Thus it may be advisable for the authors to engage with the USDA and other institutions for the purposes of producing improved weather-based yield and production forecasts. One point of note is that the predictive capacity of traditional weather forecasts is another interesting phenomenon often subject to thresholds (i.e., in some contexts, weather forecasts only become accurate relatively late in the season). Thus the authors could consider in future work when in the growing season their model might actually give useful predictions of harvest outcomes.

Long-Term Climate Change Modeling

As global and US climate models improve, particularly with regard to their capacity to predict the altered frequency of weather shocks, a model linking weather shocks to production outcomes would be useful for quantifying the agricultural impacts of climate change. Being climate change researchers, among other things, the authors will no doubt pursue this kind of research in the future.

Policy Modeling

The intuitive theory and evidence linking production shocks to stock levels—and possibly to other shock-mitigation institutions, such as futures markets, virtual reserves, and so on—suggests that this weather model could conceivably fit neatly into a larger economic model (e.g., dynamic computable general equilibrium [CGE] models) linking production, stocking behavior, financial market behavior, and trade behavior. As I and my coauthors had noted in previous work, the predictive models used prior to the 2008 food crisis very much focused on the medium to long term, and had very limited capacity to understand short-term price dynamics (Headey, Fan, and Malaiyandi 2010). Indeed, almost every cited cause of the 2008 crisis is extremely difficult to model convincingly. Headey (2010) shows the volatile and complex nature of international trade behavior, including export restrictions, but also precautionary purchases by major importers. Many authors have looked at the complexity of futures markets (see also Aulerich, Irwin, and Garcia, chapter 6, this volume), with little consensus as to their importance for price behavior. And the issue of stocking behavior is perhaps most complex of all, mixing together the endogenous behavior of private agents, some degree of public intervention, and important interactions with other factors (as we saw above). The work of Berry et al. makes a potentially important contribution by filling in one of those knowledge gaps, namely the links between weather and production shocks. But as climate change seems likely to affect the volatility of the weather (IPCC 2012), and not just secular trends, the incorporation of weather shocks into broader economic models will surely be an important area for future research. The ongoing work in this area by Berry et al. could therefore make a substantial contribution to the broader efforts to understand the causal mechanisms of food price volatility.

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