Different Slopes for Different Folks: Estimating Supply Elasticities Across Staple Grains

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October 22, 2018

1 Introduction

In their paper, Roberts and Schlenker use past yield shocks to identify supply elasticities for storable commodities. Compared to past identification strategies, this method provides a new framework in supply estimation. For example, Nerlove suggests regressing quantities on futures prices, past prices and prices predicted from an autoregressive model. Roberts and Schlenker argue that although it effectively models unanticipated supply shocks, this method suffers endogeneity stemming from anticipated supply shits. The mechanism behind their estimation strategy is that past yield shocks shift inventories exogeneously for storable commodities, which impacts futures prices and demand for storage, finally causing production changes in the future.

The two authors propose a supply and demand model of world commodity calories to estimate the effects of the U.S. Renewable Fuel Standard on world food prices. Several concerns arise regarding this research approach. First, using calorie based weights to aggregate different crops might not be appropriate in some settings. As Hendricks, Janzen and Smith (2014) point out, aggregating caloric production ignores the fact that wheat and rice are typically consumed more directly, while maize and soybeans are typically further processed or used as animal feeds. This incentivizes us to disaggregate world caloric production to the four crops that Roberts and Schlenker use to construct their calorie index, namely maize, rice, soybeans and wheat. Second, Roberts and Schlenker use calorie-weighted index of United States futures prices in their aggregated supply and demand regressions (notably excluding rice futures prices due to limited data). In addition to the concern of calorie weighted aggregation, we are also skeptical of how well U.S. futures prices can reflect worldwide anticipation of commodities prices. Hence, in a secondary analysis we narrow our scope to estimation of U.S. supply elasticity for the four commodities.

In what follows, we first describe the data that we use for this report, before discussing the methodology employed in section three. Section four is our main results. As mentioned in the above paragraph, we first disaggregate total caloric production and then focus on the U.S. market individually. In each case, we compare our results to the estimated elasticities from Hendricks, Janzen, and Smith, using similar regression models. We find that we are able to consistently estimate statistically significant supply elasticities for maize, of between 0.11 and 0.20 globally, and between 0.15 and 0.30 for the U.S. Finding significant global supply elasticities was more difficult across the other commodities, but we also were able to estimate significant wheat supply elasticities for the U.S. of between 0.24 and 0.67, depending on the specification used. Section five is a summary of our findings and discussion of some issues where further research is needed.

2 Data

We work with data from the Food and Agriculture Organizaiton (FAO), providing production data in terms of quantity, yield, and area, with production data available from 1961 to 2014 (for most countries). Following Roberts and Schlenker, we convert production data to caloric measures, but we did not aggregate production data with calorie weights. Instead, maize, rice, soybeans and wheat caloric production were calculated separately and presented in the upper panel of Figure 1 (where "aggregate" is the calorie aggregated measure used by Roberts and Schlenker). Comparing to the other three main crops, maize has experienced a higher growth rate after 2000 and has been the main contributor to aggregated production since 1961.

As in the global production panel, the lower panel of Figure 1 shows a similar upward trend of maize growth. In contrast to the observation from Roberts and Schlenker on the trend in world production, which states that fluctuations are small in proportion to the trend, US maize production experienced high volatility after 1980. While maize and soybeans

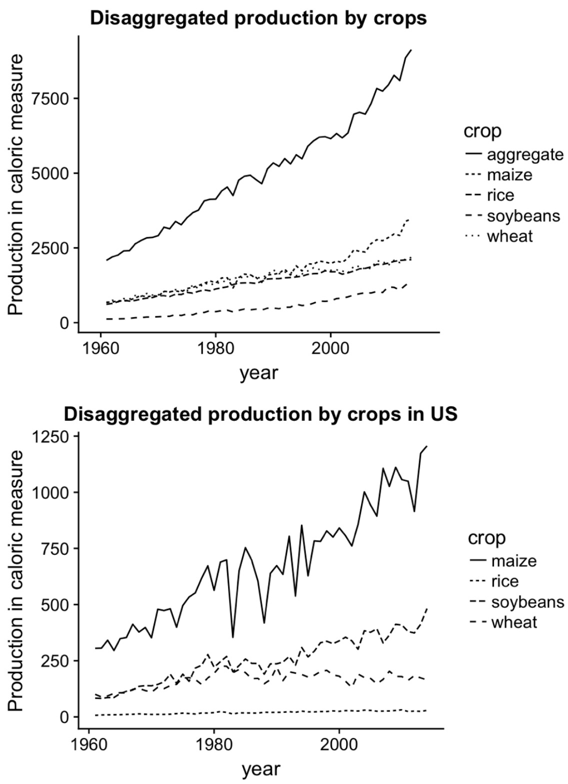

Figure 1: Caloric Production Disaggregation: Global vs. U.S.

production increases steadily in US, rice and wheat production has changed less dramatically, with a downward trend for wheat production after 1980.

In order to provide relevant covariates for the disaggregated production data, we did not aggregate futures prices with calorie weights. This of course left us with the opportunity to utilize the rice futures data, but the limitation in that data series led to difficulties in the analysis. We will discuss these issues further in section 3.

When calculating yield shock, we regressed yield on a restricted cubic spline with three knots to approximate yield trend. In our analysis we used R, and found that R and STATA yield slightly different results for the cubic splines. This occurred because R uses different formulas to generate higher order variables in regressions. In order to ensure these differences did not affect our results, we compared our calculations of the aggregate regression models to those in Hendricks, Janzen, and Smith and found that it did not change our regression results in a significant way, with any differences in outcomes far smaller than estimated standard errors.

3 Methodology

We employ similar regression frameworks to those employed by Roberts and Schlenker, though we also use the additional model added by Hendricks, Janzen, and Smith. These models are a simple OLS regression, an OLS regression with yield shock included, and a two-stage least squares regression with yield shock instrumenting for price. We use these models to ensure we have a close point of comparison between the aggregate models presented in the previous papers and the disaggregated models estimated here.

Model 1 regresses log transformed production on logged real futures prices and a restricted cubic spline with four knots. The table also presents Newey-West robust standard errors estimated with one lag. This model follows Nerlove's original concept, which deals with unanticipated supply shocks but ignores anticipated shocks. It was presented in both Roberts and Schlenker and Hendricks, Janzen, and Smith.

Model 2 includes logged yield shock in the regression from Model 1, providing an additional covariate. This model was not included in Roberts and Schlenker, but was presented by Hendricks, Janzen, and Smith. The addition of this model in the latter paper suggested that the instrumental variable approach was not actually necessary, and that inclusion of the yield shock was sufficient to identify the aggregate global supply elasticity. We aim to discover whether this interpretation holds across commodities.

Model 3 is the instrumental variables approach mentioned previously, using lagged yield shock as an instrument for the futures price in a two-stage least squares framework. This model was the main contribution of the Roberts and Schlenker paper, but was questioned by Hendricks, Janzen, and Smith. This paper attempts to find whether the instrumental variables approach may be necessary for certain commodities and less so for others.

4 Regression Results

4.1 Global Crop Disaggregation

In Table 1, we present our regression results utilizing three different estimation strategies. The results from model 1 for soybeans and wheat are small and statistically insignificant, while the supply elasticity estimates are statistically significant when we focus on maize and rice. Small sample size for rice might be a problem for the elasticity estimation. As mentioned previously, the futures price series is limited, with data only available after 1987. In addition, the limited number of observations did not allow for estimation of Newey-West standard errors for rice. In spite of this, if rice supply suffers small anticipated shock, then it is possible that control for futures prices will do all the work, i.e. purge unanticipated endogeneity.

Table 1: Estimates of World Supply Elasticities

	Dependent variable:				
	Aggregate	Maize	Rice	Soybeans	Wheat
	(1)	(2)	(3)	(4)	(5)
Model 1: OLS Omitting Yield Shock					
Supply Elast.	0.038	0.106^{*}	0.081^{***}	0.021	0.012
	(0.042)	(0.057)	(0.017)	(0.062)	(0.038)
Model 2: OLS Including Yield Shock					
Supply Elast.	0.089^{***}	0.139^{***}	0.043^{**}	0.031	0.063^{***}
	(0.017)	(0.024)	(0.015)	(0.108)	(0.024)
Shock	1.239^{***}	1.232^{***}	1.490^{***}	0.895^{***}	1.139^{***}
	(0.111)	(0.135)	(0.345)	(0.153)	(0.106)
Model 3: Two-stage Least Squares					
Supply Elast.	0.102^{***}	0.203^{***}	0.135	0.264^{*}	0.075
	(0.023)	(0.065)	(0.095)	(0.158)	(0.058)
Shock	1.291^{***}	1.269^{***}	0.311	0.935^{***}	1.160^{***}
	(0.101)	(0.146)	(1.314)	(0.126)	(0.078)
Observations	54	54	27	54	54

Note: *p<0.1; **p<0.05; ***p<0.01

Newey-West robust standard errors are presented in columns 1, 2, 4, and 5.

Model 2 and 3 include yield shocks, which were constructed in the same way as in Roberts and Schlenker's paper. As we discussed in the data section, there are slight differences between R and STATA in generating higher order knots (third and beyond). However, it did not affect results in a significant way. In model 2, only the regression for soybeans produced an insignificant estimate of supply elasticity. Supply elasticity estimates of rice and wheat are smaller than that of weighted aggregation, while maize supply elasticity is the highest among all crops. It is not surprising that maize has high and significant supply elasticity estimate as it has the highest level of production among the four main crops focused on.

Model 3 uses past shocks to yield as an instrumental variable for futures prices. We obtained different results from the previous model as soybean regression yields the largest supply elasticity. This is interesting since soybeans production is the lowest among the four crops studied. One possible explanation might be low correlation between past shocks and futures prices of soybeans. Intuitively, think of simple IV model where x and z are $n \times 1$ variables. The IV estimator can be written as $\beta_{IV} = \frac{cov(y_i, z_i}{cov(x_i, z_i)}$. If the covariance between instrumental variable and endogeneous variable is small, then the sample analog of β_{IV} will be large. In fact, in our data, the covariance between logged soybeans futures prices and lagged one period logged shocks is -0.002, which might explain why supply elasticity estimate increases dramatically after using instrumental variable. Nevertheless, the supply elasticity estimates of maize are statistically significant and greater than aggregated regression estimates in both models. In IV regression, the magnitude of maize $\hat{\beta^s}$ is twice as much as aggregated $\hat{\beta^s}$. This again might due to the high proportion of maize production in aggregated production.

4.2 US Production Disaggregation

In order to investigate to what extent the results found by Roberts and Schlenker are driven by the United States, we estimated the same three models as in Section 3.1 with data from the U.S. alone. While the results presented in Table 1 used logged production aggregated across all countries as a dependent variable, the models presented in Table 2 us only logged U.S. production as a dependent variable. However, note that column (1) still presents the results from the models estimated in Hendricks, Janzen, and Smith as a point of comparison, using aggregated data for production and yield shocks.

Table 2: Estimates of United States Supply Elasticities

	Dependent variable:				
	Aggregate	Maize	Rice	Soybeans	Wheat
	(1)	(2)	(3)	(4)	(5)
Model 1: OLS Omitting Yield Shock					
Supply Elast.	0.038	0.150***	−0.005	−0.006	0.236***
	(0.042)	(0.057)	(0.077)	(0.062)	(0.038)
Model 2: OLS Including Yield Shock					
Supply Elast.	0.089***	0.302***	−0.005	0.019	0.325***
	(0.017)	(0.024)	(0.088)	(0.108)	(0.024)
Shock	1.239***	1.343***	0.006	1.118***	1.092***
	(0.111)	(0.135)	(0.540)	(0.153)	(0.106)
Model 3: Two-stage Least Squares					
Supply Elast.	0.102***	0.272***	−0.242	0.039	0.670***
	(0.023)	(0.065)	(0.288)	(0.158)	(0.058)
Shock	1.291***	1.340***	−0.638	1.123***	1.444***
	(0.101)	(0.146)	(0.962)	(0.126)	(0.078)
Observations	54	54	27	54	54

Note: *p<0.1; **p<0.05; ***p<0.01
Newey-West robust standard errors are presented in columns 1, 2, 4, and 5.

In general, we find that estimates for the supply elasticities for maize and wheat are statistically significant across all three models. Estimates for rice are not statistically significant in any model, and only the yield shock coefficients are significant for soybeans in the latter two models. It is not surprising that maize and wheat estimates are significant for the U.S. while rice estimates are insignificant, since both maize and wheat are major crops relative to rice which is a more minor crop.

However, this does not explain why estimates are insignificant and small for soybeans, which have seen increased production in recent years in the U.S.

For maize, in models 2 and 3 we estimate a supply elasticity of between 0.27 and 0.30, with both estimates falling well within the confidence interval of the other. This estimate also makes sense, as the U.S. produces about one-third of the world's maize, and this estimate is about three times the estimates found by Roberts and Schlenker. Additionally, as suggested by Hendricks, Janzen, and Smith this is further evidence that using instrumental variables in this case may not be necessary, as the inclusion of the yield shock variable in model 2 does just as well as the instrumental variables approach in model 3.

However, the same cannot be said in the case of wheat. For maize, models 2 and 3 provided similar point estimates that were statistically different from the estimate produced by model 1. In contrast, for wheat the estimate of 0.33 produced by model 2 only just outside of the 95 percent confidence interval of the estimate of 0.24 from model 1, but the estimate of 0.67 produced by model 3 is far beyond either of the other two estimates. As suggested previously, this could be due to low covariance between wheat yield shocks and futures prices, but this may also suggest that in the case of wheat the instrumental variables approach was necessary. This difference between maize and wheat could be because of the substantial variations in maize production seen in Figure 1, suggesting that yield shock alone may provide sufficient identifying variation for maize, while the more steady production of wheat meant that the additional inclusion of yield shock in model 2 was not sufficient to identify the supply elasticity.

Estimates for rice and soybean supply elasticities are insignificant across the board. For rice, we are again limited by fewer observations in the futures price series, but it is also likely that the low level of variation in U.S. rice production makes it difficult to nail down an estimate. Examining U.S. rice production over time as presented in Figure 1 does suggest that an estimate of no response to price may not be far from the truth. In contrast, finding no significant estimates for soybeans is surprising, given their increased prevalence in U.S. agriculture in recent years. Additionally, due to the relationship between maize and soybeans through crop rotation patterns, it is strange that a strong estimate of maize supply response would not be coupled with a similarly strong estimate for soybeans.

5 Conclusion

Our analysis has utilized three regression frameworks, two OLS models and one utilizing instrumental variables, to estimate supply elasticities for maize, rice, soybeans, and wheat for both an aggregate of global supply and the U.S. alone. In all cases we were able to produce statistically significant estimates for maize, while significant estimates were also found for wheat, rice, and soybeans depending on the model and context. In general, the estimates that were statistically significant were larger than those estimated by Roberts and Schlenker, and in some cases much larger.

In comparing results from estimating the U.S. elasticities to the elasticities estimated for global supply, we find very different results, especially for wheat. The wheat supply elasticity estimated with U.S. data using model 2, about 0.33, is over five times as large as the estimate global wheat supply elasticity from the same model, 0.06. This suggests that wheat production in the U.S. is much more responsive to price than in the rest of the world, or that there are many countries with a perfectly inelastic supply leading to a lower aggregate estimate. Similar, though less extreme, differences are clear when comparing estimates of the maize supply elasticity between the U.S. and global aggregate. It is possible that these supply elasticities are higher in the U.S. than in other countries due to greater availability of storage, or due to farm support programs which allow for payments on idle land allowing some land to be taken out of production in a given year. As Hendricks, Janzen, and Smith suggest this larger price response could simply be due to the relevant U.S. futures prices used in the model, prices which U.S. farmers would be more reactive to than farmers in other countries.

While the elasticities we were able to estimate significantly were larger than those estimated by Roberts and Schlenker, they are still very small, suggesting that supply for any of these four commodities is highly inelastic. Of course, this could suggest that these frameworks, initially developed by Roberts and Schlenker and expanded upon by Hendricks, Janzen, and Smith and this analysis, are only capturing short-term supply response. Depending on the length of run being captured by these analyses, this could be as short as a within-season response, in which case planting decisions, and therefore supply, may be largely set. Even if these models capture a yearly supply response there may be little room to adjust what farmers have planned, such as planned crop rotations for upcoming years, only changing for substantial fluctuations in price, which would lead to an inelastic supply.

If further research could focus on modeling a long-run supply response, then we could more effectively determine the length of run captured by the models in this analysis. A model which could represent multiple lengths of run could also help to indicate how farmers transition from rigid short-term decisions to more flexible planning in the long-run.

6 Reference

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