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The Use of Price Elasticity to Estimate Future Volatilities in Stochastic Simulation: an Application to the Korean Rice Market*

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Keywords

aggregate measurement of support, future volatility, Korean rice market, price elasticity, stochastic partial equilibrium model

Abstract

Stochastic methods, which random draws on selected exogenous variables of an economic model, generate outcomes for the endogenous variables, are used to capture enough potential outcomes. This stochastic output should reflect historical data in terms of variable levels and variation. Two methods to match historical variation are explored: 1) increasing the variance of error terms of either supply or demand equations causes higher variance in simulated price and quantity, and 2) more elastic demand decreases price variation and increases production variation. A Korean rice market model is used for this stochastic simulation process to test these ideas. The results imply that the elasticities can be used to fit or calibrate model variation to historical variation. The model adjusted by price elasticity provides the possible range of the Aggregate Measurement of Support (AMS). The result shows that there is no possibility of exceeding the total AMS. Our work begins to consider how to improve model performance relating variation, not just levels, thus enabling applied economists using this approach to speak more directly to concerns about market risk and uncertainty.

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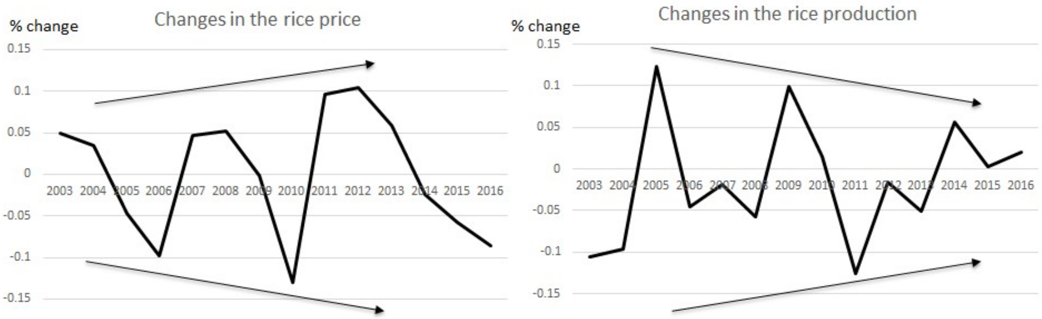
1. Introduction

A structural economic model for agricultural projections based on point estimates cannot capture enough potential outcomes in many cases (Westhoff et al. 2006). A point estimate is an approximate value of random samples. In the structural economic model, point estimates can be the mean of the residuals. The deterministic simulation generates output data from a single observation, such as the mean of the residuals in each period. Hence, these inputs generate a single value for each endogenous variable in each period and do not illustrate any ranges of outcomes based on key sources of uncertainty. In contrast, stochastic simulation can be used for applied market projections, generating ranges of endogenous variables based on ranges of exogenous variables. Subsequent simulations using the same ranges of exogenous variables and different policy assumptions estimate how the policy change affects producers, consumers, and taxpayers over a range of market contexts. The question of how best to make stochastic simulation output match historical data, especially variable variation, has not been carefully considered in the literature focused on stochastic partial equilibrium models of agricultural commodity and related markets.

Our study uses a stochastic equilibrium model to investigate the use of error terms and price elasticities in improving the match between simulated and historical market volatility. The Korean rice market is chosen for our experiment. Figure 1 suggests that Korean rice price volatility has increased (5% in early 2000 to 10% in early 2010), while the volatility of Korean rice production has slightly decreased over time (10% in early 2000 to 5% in early 2010). When we only consider the magnitude of volatility, price volatility is more substantial than production volatility. These volatility patterns should be reflected in the stochastic outcome. The structural model consists of behavioral equations representing the supply, demand, and other decisions, as well as identities. One crucial fact is that imports are primarily constrained by import policy, so trade quantity changes might not be a source of domestic market volatility. Another relevant aspect of this specific case is the timing of supply decisions: area planted to rice is the key supply decision, but the decision is made before the start of the marketing year. Given the delay between planting during the previous marketing year and production at the start of the current marketing year, the elasticity of supply cannot be adjusted to affect the price volatility within a year. Instead, the price volatility within a year will depend on shocks to production, on-demand shocks, and demand elasticity. Hence, changing supply elasticity in the harvested area equation might not be reasonable to reflect the historical volatility pattern.

Figure 1. Variability patterns in the Korean rice price and production (% change).



This structural model is used in this study to emphasize the role of the error terms and price elasticities when we estimate future market volatilities concerning historical data. Two methods to match historical variation are explored: 1) changing the variance of error terms of either supply or demand equations causes like change in the simulated price and quantity variances, and 2) changing demand elasticity has opposite effects on price and quantity variation. The Korean rice market model used for this stochastic simulation process tests these ideas. Elasticities of demand and supply are from the Korean Agricultural Simulation Model by the Korean Rural Economic Institute (Han et al. 2015). They estimate and calibrate, if necessary, elasticities to make agricultural projections. There are at least two advantages of using this model. First, this model is maintained and used by the Korea Rural Economic Institute (KREI) for policy analysis to inform decision making (Han et al. 2015). Second, the outcome of this exercise shows how an existing model can be improved by applying criteria relating to variability, in which stochastic variations are reflected in historical variations, as well as levels of variables. A Monte Carlo process is used to generate 500 stochastic outcomes of Korean rice price and production. We use the two supply and demand errors and the demand elasticity to force stochastic output variation to match the variation in historical data. Finally, we provide a range of simulated Aggregate Measurement of Support (AMS) as a key indicator to assess the implications of the exercise.

The article is structured as follows. The next section introduces the empirical framework. In the third section, the data and the calibration method are presented. The resulting volatility of key endogenous variables from the stochastic projection process is reported in the fourth section. The last section summarizes and discusses our findings.

2. Background of a stochastic analysis

Stochastic analysis can be based on Monte Carlo methods (Westhoff et al. 2006) in that random draws on selected exogenous variables of a structural economic model generate many outcomes for the endogenous variables. For instance, applied analysis of agricultural and related markets and policies generates many hundred stochastic outcomes from random draws from empirical distributions of input variables so that results can represent price, yield, and quantity variation, as well as ranges of taxpayer costs, farm income, or other indicators (FAPRI-MU 2011; OECD-FAO 2017). Stochastic models have been used in various commodity markets (Thompson et al. 2010; Chavez and Wailes 2011; Fadiga et al. 2008; Soon et al. 2019; Westhoff and Gerlt 2013). These articles use structural economic models and random draws on a subset of the exogenous variables to introduce uncertainty, broadening the relevance of their analysis, and showing how policies perform in a variety of contexts. An alternative approach, based on Gaussian quadrature, has also been used to test model sensitivity to assumptions, but this method might be best applied in instances where the model response tends to be smooth (Arndt, 1996; Preckel et al., 2011; Stepanyan et al., 2019). In contrast, many of the studies of policies sited here focus on the implications of policies that are market sensitive, such as subsidies that are triggered when the market price crosses some trigger level or an import quota. Such policies are suspected of causing sharp changes in market response to shocks at these triggers or quotas.

Stochastic partial equilibrium model simulation is used to analyze policy impacts in many applications. Babcock (2012) examines the market impacts of changes in the U.S. biofuels policy. The author uses means and volatilities of exogenous variables, specifically gasoline and diesel prices and crop yields, to generate stochastic outcomes for U.S. maize and ethanol markets. Westhoff et al. (2006) and Glauber and Westhoff (2015) estimate the U.S. Aggregate Measurement of Support (AMS) using a stochastic partial equilibrium model. Selected exogenous variables for supply and demand are varied and the results estimate a range of U.S. AMS. Authors find that the estimated U.S. AMS using deterministic analysis is lower than the average AMS generated using stochastic analysis. Soon et al. (2019) estimate the impact of possible rice import if the over-quota tariff rate is reduced using the stochastic partial equilibrium model. In consideration of the three cases, these articles use stochastic partial equilibrium analysis to estimate not only the level of expected outcomes but also the variability of outcomes. However, this use of the model is best supported if estimated variability reflects reality.

Ideally, the stochastic output should reflect historical data in terms of variable levels and variation. The question of how best to make stochastic simulation output match historical data, especially variable variation, has not been carefully considered in the literature focused on stochastic partial equilibrium models of agricultural commodity and related markets. For example, increasing or decreasing variation in the exogenous data, such as equation errors, leads to an increase or decrease in variations of both the stochastic price and quantity. If stochastic output variation for price and production both are either lower or higher than historical variation, increasing or decreasing the absolute magnitude of the equation errors can help to fit historical variation. However, if the comparison to historical variation is mixed, with simulated output for one variable more volatile than historical data and the other less volatile, adjusting equation errors cannot be used to calibrate the model to reproduce historical variation of both prices and production.

Adjusting price elasticities could be an alternative way to improve the ability of the simulated model to match the pattern of historical variations. Baumeister and Peersman (2013) illustrate that an increase in oil price variation and a decrease in oil production variation can be reproduced by allowing for time variation in the supply and demand price responsiveness. The relevance to the present exercise is that key elasticities of a structural model can be used to help simulated data match historical market variation. An elasticity change can have different impacts on the variation of output variables, increasing some and decreasing others, in contrast to the common effect of the equation errors. In at least one case, the role of elasticities has been exploited in the way we propose: Beckman et al. (2011) compared simulation results of crude oil volatility with historical data as a means to calibrate elasticities. The price volatility in the historical data is initially higher than the simulated price volatility from the GTAP-E (Global Trade Analysis Project-Energy and Environment) model that is a general equilibrium model. Therefore, the authors reduce demand elasticities for oil products so that the simulated price volatility corresponds more closely to historical price volatility.

3. Empirical framework

3.1. A theoretical model

A theoretical model is introduced to emphasize the role of the error term and price elasticity in determining the variation of endogenous variables. The Korean rice market can be represented by demand and supply equations and the market-clearing identity (Baumeister and Peersman 2013):

(1) $Q_t^D = -d_t \bullet P_t^* + \varepsilon_t^d$ and

(2) $Q_t^S = s_t \bullet P_t^* + \varepsilon_t^S$,

(3) $Q_t^D = Q_t^S$

where Q_t^D and Q_t^S are rice demand and supply, respectively. P_t^* is the equilibrium price. Quantity and price variables are in logarithmic form. Hence, d_t and s_t represent price elasticities. Because of the negative sign in the demand equation, both these parameters are assumed to be positive, although the demand elasticity is consequently negative. Regarding the error terms, we assume that $E(\varepsilon_t^d) = 0$, $E(\varepsilon_t^s) = 0$, $E(\varepsilon_t^d)^2 = \sigma_{d,t}^2$, and $E(\varepsilon_t^s) = \sigma_{s,t}^2$. We also assume that there is no correlation between error terms, $E(\varepsilon_t^d \varepsilon_t^s) = 0$. In reality, supply and demand errors can be correlated, $E(\varepsilon_t^d \varepsilon_t^s) = \sigma_{d,s,t}$.

The theoretical model is solved to generate the equilibrium of price, P_t^*, and quantity, Q_t^* as follows

(4) $P_t^* = \dfrac{\varepsilon_t^d - \varepsilon_t^s}{s_t + d_t}$ and $Q_t^* = \dfrac{s_t \varepsilon_t^d + d_t \varepsilon_t^s}{s_t + d_t}$.

The equilibrium of price and quantity are functions of the demand and supply errors and price elasticities. Through this equilibrium, we can derive the variability of Korean rice price and production as follows:

$$(5)\ E(P_t^*)^2 = \frac{\sigma_{d,t}^2 + \sigma_{s,t}^2}{(s_t + d_t)^2} \text{ and } E(Q_t^*)^2 = \frac{s_t^2\sigma_{d,t}^2 + d_t^2\sigma_{s,t}^2}{(s_t + d_t)^2}.$$

Depending on error variances and price elasticities, the Korean rice price and quantity variations are changed. A change in the variance of Korean rice demand or supply errors has a positive effect on the variance of the price and quantity.

$$(6)\ \frac{\partial E(P_t^*)^2}{\partial \sigma_{s,t}^2} > 0 \text{ and } \frac{\partial E(Q_t^*)^2}{\partial \sigma_{s,t}^2} > 0,$$

$$(7)\ \frac{\partial E(P_t^*)^2}{\partial \sigma_{d,t}^2} > 0 \text{ and } \frac{\partial E(Q_t^*)^2}{\partial \sigma_{d,t}^2} > 0.$$

Conversely, decreasing the size of the variance in either demand or supply errors leads to decreasing variations of both price and quantity. Hence, if assessed in terms of model calibration, adjusting the variance of the error terms might be appropriate if the variation of both simulated price and quantity are both larger or smaller than the variation of historical data.

A change in price elasticity generates inverse effects on the price and quantity.

$$(8)\ \frac{\partial E(P_t^*)^2}{\partial d_t} < 0 \text{ and } \frac{\partial E(Q_t^*)^2}{\partial d_t} > 0,$$

$$(9)\ \frac{\partial E(P_t^*)^2}{\partial s_t} < 0 \text{ and } \frac{\partial E(Q_t^*)^2}{\partial s_t} > 0,$$

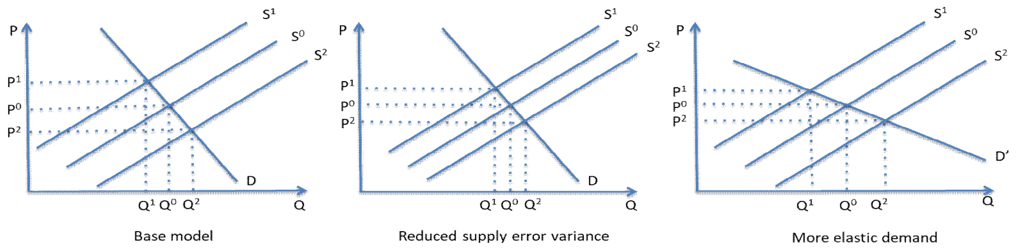
An increase in price coefficient of either demand or supply causes a decrease in the variability of the price and an increase in variability of the quantity, and a decrease in the supply or demand coefficient implies the opposite impacts. Because the demand equation uses the negative of the price effect, the assumed positive coefficient in this equation corresponds to a negative own-price elasticity of demand. So an increase in this coefficient implies more elastic demand, just as an increase in the supply equation price coefficient corresponds to a more elastic supply. These calculations that more elastic market response tend to imply faster quantity adjustment and a limited range of price outcomes is by no means new, but takes on a new usefulness when calibrating model outcomes to match historical variability in these variables. This pattern suggests that adjustment to elasticities can be a means to match variability of the price and quantity in historical data if the stochastic output for one variable is more volatile than the historical data and the stochastic output of the other variable is less volatile than the historical data.

3.2. Stochastic approach

A stochastic approach is used to examine the implications of uncertainty. We randomly draw from distributions of selected exogenous variables to generate 500 outcomes for the endogenous variables using a structural economic model.

We calibrate the model using two of the available parameters. The focus of this exercise is the supply error and demand elasticity (figure 2). Analysts might need to adjust price and quantity variations if simulated variations do not reflect historical values. In this example, the simulated price variation is assumed to be higher than the historical variation. One method for calibration is to decrease or increase the supply or demand errors that are used to drive the Monte Carlo simulation. In the figure, the possible uncertainty range between S^1 and S^2 is narrowed. Then, the simulated variation of the price (P) and quantity (Q) are also reduced relative to the variation of two variables in the base model. The second method is to increase or decrease price elasticity in the demand or supply sides. If the price elasticity of demand is more elastic than the base model, then the variation of the price (P) is reduced and the variation of the quantity (Q) is increased relative to the base model. Hence, these two methods to reduce simulated price variation in order to calibrate results to historical price variation have opposite effects on the variation in quantity. This pattern can be exploited to calibrate an existing model to address questions of market variability, as shown in the following application.

Figure 2. Calibrating a stochastic partial equilibrium model output variance by adjusting supply error or demand elasticity



4. Application

The Korean rice market is chosen as a good case for our experiment. The model is based on annual data from 1997 to 2017. Domestic production such as area harvested and rice and soybean yields are from Statistics Korea (KOSTAT) and domestic demand such as consumption, ending stock, and rice and wheat prices are from Food Information Statistic System (FIS). Import quantity and price are from the U.S. Department of Agriculture Production, Supply, and Distribution (USDA-PSD). Macro variables such as Gross Domestic Product (GDP), Population, and Consumer Price Index (CPI) are obtained from the Bank of Korea.

Table 1 shows the Korean rice model structure. Elasticities of demand and supply are required to construct the structural model and are taken from the Korea Agricultural Simulation Model (KASMO) developed by the KREI. Elasticities used in this study are available on request from authors. The supply elasticity concerning rice return is more elastic than soybean return. The demand is inelastic with respect to income, presumably because of the role rice plays in this developed country.

The import equation is a complementary slackness condition to represent the Tariff Rate Quota (TRQ) regime implemented in 2015. A Fischer-Burmeister representation of a nonlinear complementarity problem is used (Fischer 1992). The representation allows imports to exceed the Minimum Market Access (MMA) quantity, which is 408 thousand metric tons, if the price of the imported price with the 518% over-quota tariff rate is lower than the price of domestic rice.

Korean rice policy includes direct payments consisting of fixed and variable components. These variables are added to the domestic rice returns that drive the harvested area equations. The fixed direct payment is 16,393 won per ha. The variable direct payment equals the difference, if positive, between the target rice price and the sum of the fixed direct payment and the market price times 85%. The target rice price is 188,000 won per 80 kilograms. If the farm price is below the target price and the gap multiplied by 0.85 is higher than the fixed direct payment, then the total variable direct payment is calculated by multiple of area harvested and 65 (10,000 won) as unit payment per ha based on the government decision. The variable direct payment used in our model is a payment per ha that is imposed in the harvested area. The variable direct payment is the main component of the total AMS, but total direct payment is not considered in the harvested area equation of the model.

Table 1. Korean rice model structure

(1) Direct payment = Fixed direct payment + Variable direct payment
(2) Variable direct payment = max(0,(target price-farm price)*0.85 - fixed direct payment)
(3) Domestic rice return = Domestic price + Direct payment
(4) Harvested area = f(lag of harvested area, lag of domestic rice return, lag of domestic soybean return)
(5) Yield = f(trend)
(6) Per capital domestic rice consumption = f(domestic rice price, domestic wheat price, real GDP per capita)
(7) Ending stock = f(lag of ending stock, domestic rice price)
(8) Import: a Fischer-Burmeister representation of a nonlinear complementarity problem (NCP) function

$$\sqrt{[Import - MMA]^2 + [Price\,at\,the\,quota\,tariff - Domestic\,price]^2}$$
$$-[Import - MMA] + [Price\,at\,the\,quota\,tariff - Domestic\,price] = 0$$

(9) Market clearing: Harvested area*Yield + Beginning stock + Import = Domestic rice consumption + Ending stock

The model is projected to estimate market conditions in 2018-2021. Projection period values for the exogenous variables, which are corn and soybean yields and wheat price, are drawn from a KASMO projection (Seo and Kim 2016). Substitute commodities such as corn, soybean, and wheat are considered in the model because they can cause the demand and supply sides in the Korean rice market. Forecast values for the gross domestic product (GDP), population, and the consumer price index (CPI), 2015 base year, are from IHS Markit (2016). Fixed direct payment, the target price, and MMA quantity are held at their 2017 values. Given these assumptions about the exogenous variables, empirical distributions are generated. We then take 500 random draws from the empirical distribution, including errors of harvested area, yield, domestic consumption, and ending stock. These 500 market outcomes represent possible outcomes and volatilities of price and quantity in the future.

We generate a range of simulated AMS as a key indicator to assess the implications of the exercise. The Korean government committed to AMS limits under the Uruguay Round commitment (Choi et al. 2016). A deterministic projection of the AMS might remain well below the limit if recent market conditions and policies are used as a guide. However, it is theoretically possible for support to exceed the limit under sufficiently extreme circumstances. Policymakers could be better informed by simulation output that reflects how AMS varies according to conditions, such as when weather causes yields to be very high or low. In particular, the stochastic analysis that has been shown to usefully inform U.S. policymakers of the risk of that country exceeding its AMS limits could be applied to the politically sensitive case of Korean rice policy. In this paper, stochastic partial equilibrium analysis generates a range of the total AMS based on changes in certain exogenous variables. The stochastic mean AMS is found to depend critically on the outcomes when certain thresholds are exceeded, so the average value depends on extreme outcomes. As such, the model calibration method that explicitly compares projected and past volatility of price and quantity is a critical input into this process.

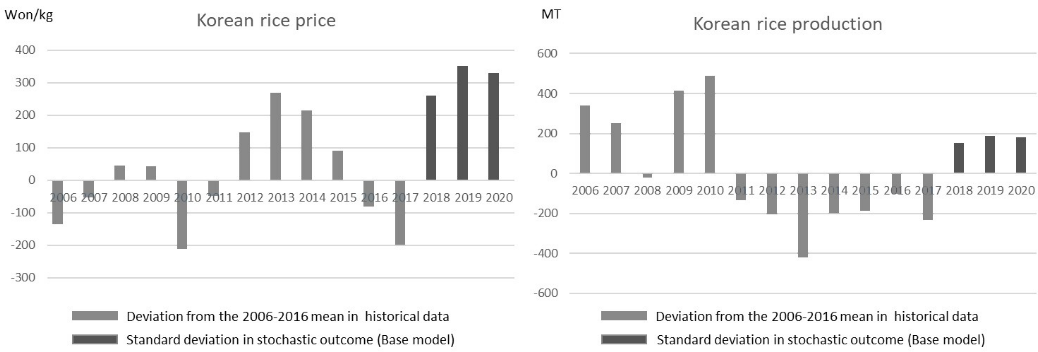
5. Empirical results

5.1. Base model results

The stochastic output of the base model does not reflect the historical variation (Figure 3). The standard deviations of price and production of the base model are generated from the 500 model simulations. As noted earlier, these are Monte Carlo simulation outcomes from the model with random draws from empirical distributions for the supply and demand equation error terms. The price variation in each year in the historical period is less than the variation of the projected price of the stochastic simulations. For instance, the standard deviation of the stochastic Korean domestic rice price suggests a projected pattern that is not reflected in the historical period: the projected standard deviation of the price is 400 won per kilogram in 2017 whereas past deviations from the 2006-2016 mean have never been this large. In a case of the Korean domestic rice production, the standard deviations in projected years appear small as compared to historical patterns. Projected standard deviations would appear to underestimate the full range of possible outcomes. There are deviations of over 400 million tons in 2010 and 2013, but stochastic production in the base model indicates that a deviation of over 400 million tons is very unlikely.

The base model can be calibrated through adjustments to the error terms and elasticities, as noted earlier. Here, decreasing the variation of Korean rice price and increasing the variation of the Korean rice production is necessary if the model output variability is to correspond more closely to historical variability. In the next section, these two approaches are used to demonstrate this method to calibrate the model using Korean domestic rice price and production variability.

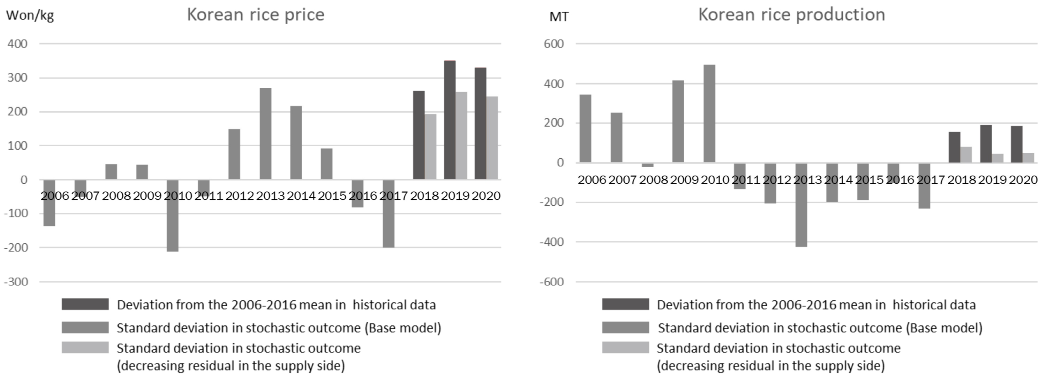
Figure 3. Stochastic price and production in the base model



5.2. Reducing the supply variation results

Reducing the supply variation decreases the variation of the simulated price and production, as mentioned above (equation 6). Figure 4 shows the standard deviations of the stochastic price and production if the supply error variance is reduced as compared to the variance in the base case, as well as the historical variance. The standard deviation of the rice yield residual is reduced by 50 percent relative to the original variation of the rice yield. As a result, the range of possible outcomes for the Korean rice price is narrowed. The range of Korean rice production is also smaller relative to the range in the base model. And it is reduced even further as compared to historical variation in this variable. If the rice production variation is changed, alone, then the calibration process might be satisfied for one of these two variables while causing the apparent error in the distribution of the other variable to become only more severe.

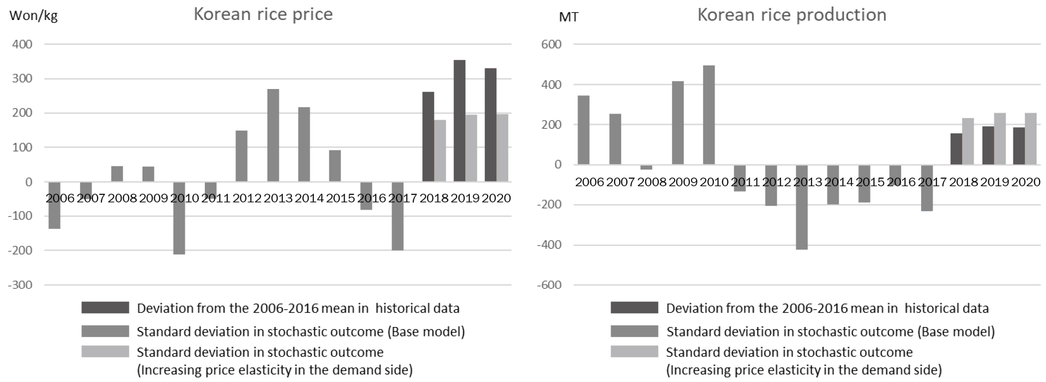
Figure 4. Changes in simulated price and production variation after calibration only by changing the supply error



5.3. Increasing the price elasticity of demand results

Increasing the price elasticity of demand plays a different role in determining the variation of the price and production. Figure 5 illustrates how more elastic demand affects the variation of the simulated price and production results, as well as historical production variation. The price elasticity of demand in the base model is -0.29. In the calibration experiment, the price elasticity of demand is set to -0.6. The consequences of this change on the price and production output of the model are consistent with Equation (8).

Figure 5. Changes in simulated price and production variation after calibration only changing the demand elasticity



This approach causes simulated model output to fit the pattern of historical data. Stochastic price outcomes are less volatile than in the base model and closer to the volatility observed in historical price data. The simulated variability of rice production is more significant than in the base model after this change and consequently closer to historical volatility. Hence, simulated data that are calibrated based on this approach are more likely to reflect the variation in the historical data.

Approaches introduced above generate different ranges of rice prices and production in Korea. In the case of the Korean rice market explored here, the base model estimated the price to be more volatile in the future than historical data suggest, and the production was estimated to be less volatile than seen in historical data. Table 2 summarizes changes in price and production variation when we reduce the supply variation and increase the demand elasticity. The standard deviation is used as the measure of variation. The results show that increasing the price elasticity of demand makes rice production more volatile and reduces price variation while reducing the supply error variation reduces both variations in the price and production for 2018-2020, compared to historical variation from 2006-2017. Hence, adjustment of the price elasticity of demand is a better way to calibrate results rather than adjusting supply-side error terms. Beckman et al. (2011) also use demand and supply elasticities to modify the volatility in oil product outputs. The percentage change in oil product outputs is used to match the historical outcome. Our study uses demand elasticity to change the volatility of price and outputs as checking the percentage change in outcomes. A difference between Beckman et al. (2011) and our study is that Beckman et al. (2011) use the general equilibrium model, and our study is based on the partial equilibrium model.

Table 2. Comparisons of variation between historical and stochastic data

	Historical data	Stochastic data					
	2006-2017	2018		2019		2020	
	s.d	s.d	% change	s.d	% change	s.d	% change
Base case							
Production (MT)	249.4	166.0	-33.5%	192.5	-22.8%	184.7	-25.9%
Price (Won/kg)	128.4	302.7	135.7%	370.5	188.6%	345.6	169.1%
Reducing the supply error case							
Production (MT)	249.4	100.5	-59.7%	101.8	-59.2%	99.9	-59.9%
Price (Won/kg)	128.4	208.6	62.5%	254.1	97.9%	239.7	86.7%
Increasing the price elasticity of demand case							
Production (MT)	249.4	207.3	-16.9%	220.7	-11.5%	217.9	-12.6%
Price (Won/kg)	128.4	202.3	57.6%	209.1	62.9%	207.2	61.4%

Source: Authors' calculations. s.d. represents the standard deviation. The % change is calculated by the difference between a current year's value and historical value.

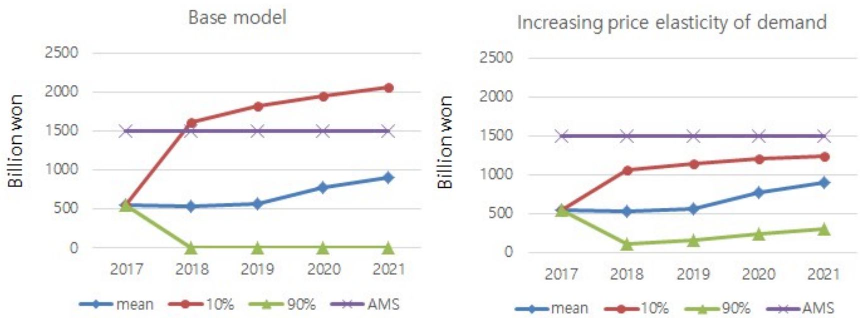
5.4. Stochastic AMS

To consider the potential implications of these two approaches to model calibration, we calculate the AMS for Korean rice. As noted earlier, a reduction in the rice price can trigger variable direct payments, and, if so, then the total AMS could increase. There is, in theory, the potential that these increases in rice support could cause AMS to exceed Korea's commitment. Therefore, it is vital to consider the total AMS in the context of plausible market uncertainty.

The deterministic point estimate of the future AMS might fail to represent market conditions that trigger the variable payment. The model is simulated deterministically, without any draws on exogenous variables. In this case, the estimated total AMS in 2017 is 539 billion won, which is well below the AMS limit (1,490 billion won). Since the Korean rice price falls in the projection period, the variable direct payment plays a role in the total AMS. However, the deterministic value does not reflect explicitly the outcomes where the rice price is high, so there is no variable direct payment, nor potential outcomes with even lower rice prices and higher variable direct payments. Turning to stochastic simulation, with the additional step to calibrate to the variations of key output variables, allows the calculation of AMS over a range of market conditions.

The total AMS projected by the model using this stochastic process with calibration suggests a potential for AMS to exceed the limit that is not detected by deterministic analysis (Figure 6). However, the results depend on the calibration method. Since the second method that handles demand elasticity is fit to the model, consider the case that demand elasticity is used to calibrate the model. In contrast to the base model case, none of the estimated AMS from the stochastic model simulation results total AMS exceeds the commitment given this calibration method. Given that the second calibration method that uses demand elasticity is shown to match better historical variation, this set of results with no share of AMS outcomes exceeding the commitment level seems a more appropriate indication of projected market conditions and their policy implications at this time.

Figure 6. The stochastic projection of the total AMS after calibration by changing both supply error and demand elasticity.



6. Conclusions

Stochastic simulation of a partial equilibrium model is used to generate many outcomes that describe a range of possible market conditions. In contrast, deterministic simulation of such a model produces only a single outcome. Stochastic simulations are allowed for some of the variations in actual markets to appear in applied market and policy analysis. While by no means an all-inclusive method that can account for all sources of risk, stochastic simulations allow for researchers to take account of at least some of the uncertainty that is typically ignored or understated in the deterministic analysis. Here, we consider historical price and quantity variations, in particular, using variability as a means to calibrate a model and then using stochastic simulations of the model to estimate outcomes of policy. We take the case of the Korean rice market for our exercise.

We examine two approaches for model calibration based on the variability of output: the variation in the supply shock or error, and the price elasticity of demand. The idea, as illustrated mathematically, is to use these two parameters to force the variation of a model to match the historical variation of key variables. We apply the idea to our specific model that is already used to support decision making by estimating policy impacts on markets. Starting with parameters used in the existing KREI-KASMO model for the Koran rice market, stochastic price and quantity variations are not consistent with historical values. In this example, stochastic price variation is more substantial than historical price variation, while stochastic quantity variation is smaller than historical quantity variation. In this case, increasing the price elasticity of demand makes stochastic price and quantity variations closer to historical values.

This calibration discussion highlights the potential trade-offs and implications of taking into account variation in key variables in the applied economic analysis of future policies or policy conditions. However, we also recognize several limitations. First, we do not consider the potential that both the variation in these key variables and the levels of these key variables could be targeted at the same time. Ideally, statistical methods that fit first and second moments, at least, could be exploited initially. However, it is not always clear that the parameters of existing models have been developed on such a basis. Even so, reconciling the presumed need to target level and variance simultaneously could be emphasized. Second, more error terms and elasticities could be considered, even if the initial values or distributions are taken as given. For example, ending stocks equation error terms or elasticity could be considered. Third, there could always be more stochastic elements, such as other commodity prices, macroeconomic variables, or even model coefficients and even equation structure. Fourth, the trade-offs could be expressed more clearly in terms of an explicit loss function. The degree of "fit" could be represented mathematically, with deviations from levels and variances of output data relative to historical data assessed through strict application of an explicit loss function. Fifth, this comparison might ideally be conducted by simulating the model over the historical period and applying this loss function over the same contextual factors, such as macroeconomic and policy variables, before extrapolating to future market conditions. Thus, while we stress that the methods explored here offer the potential for applied economists to calibrate an existing model, an ideal examination might be a much more elaborate effort that begins from the start with this goal in mind. In practice, however, we expect that many efforts to provide more robust stochastic simulations for policy analysis might adapt an existing and already used model as we do in this exercise. Moreover, such an effort requires investments in resources that might well be beyond the reach in some or many instances.

The comparison of estimated AMS levels to commitment levels show that stochastic analysis has a role, and calibrating the model to match historical variation can affect policy relevant results. Indeed, in the example presented here, the share of projected outcomes in which Korean AMS, driven by rice subsidies and barrier to imports, exceeds its commitment depends on if and how the model is calibrated. Without calibration, some share of outcomes result in AMS exceeding the country's WTO commitment, whereas this share falls to zero if the model is calibrated to reproduce historical variability. While this test is conducted for only one case, the implication is that stochastic model simulations without considering, first, the validity of the simulated market variability could cause misleading results.

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