Downside risk of major crops in selected six regions in North Dakota

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Abstract: This paper investigates downside risk by utilising the value at risk (VaR) in the context of selected three different commodities, specifically corn, soybean, and hard red spring wheat (HRSW) in North Dakota (ND). This study finds that the downside risk of crop net return is significantly different in six different regions in ND. Growing corn in the North East region is estimated to has the highest risk, whereas the South Valley region has the lowest risk compared. Growing soybean in the North East region has the highest risk, whereas the South Valley region has the lowest risk. Lastly, growing HRS wheat in South Central has the highest financial risk, whereas the South Valley has the lowest risk. The highest risks are stem from the raising of corn and soybean in the production of the crop in the North East and raising the HRS wheat in South Central.

Keywords: stochastic dominance; value at risk, VaR; downside risk.

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1 Introduction

Deaton and Laroque (1992) stated that commodity prices are very volatile. Their research focus was on the behaviour of commodity prices. Commodity prices are very sensitive to a wide range of variability in the market. Some commodity prices frequently vary from month to month, vary from day to day, vary from hour to hour, and vary from minute to minute – their statement has been proven by the current situation, where commodity price is extremely volatile. Commodity price has been reached very high in mid-2008, and the last two or three years (Wilson and Miljkovic, 2013). However, the price did not stay as it was. Today, farmers have a headache from the uncertainty of price and risk associated with specific commodities.

Supply and demand are essential to determine many different economic aspects. However, most important economic aspects are demand, which is known as a quantity of demand for producer perspective. Moreover, the performance of the competitor directly impacts the demand volume shared with producers, and the performance of competitors is essential to the local producers today. Another important economic factor is the currency value. Implicitly, this is referring that domestic producers or farmers have high business risk, which is the exposure of a company or organisation to where the factors that will lower the business profit or lead it to fail.

High business risk generated by three primary sources: market sources (price volatility, uncertainty quantity of demand, and currency inflation), biophysical environmental sources (crop yield variation, weather variability, and production variability), and last one is an internal factor (investment decision, fixed cost, the variable cost, and management skills) (Gabriel and Baker, 1980). The correlation between business risk and financial risk is negative (Collins, 1985), which means that the policymakers concerns about the financial risk and resolve the pressure off from financial risk by implementing the Farm Bill 179 or other policy regulations. Those policies may not resolve any pressure off from business risk (Gabriel and Baker, 1980). In this regard, financial risk happens if a business cannot meet its obligations to pay back its debts (Gabriel and Baker, 1980).

Therefore, the objective of the paper is to investigate the downside risk of business by utilising the value at risk (VaR) in the context of selected three different commodities that grown in North Dakota (ND): corn grain, soybean, and hard red spring wheat (HRSW). Further, the paper is also to utilise the stochastic dominance approach to evaluate the selected six different regions by each distribution of net crop revenue.

The paper hypothesises that if a farmer has a high fixed cost as business risk, then each net crop revenues would be relatively small, as well as VaR estimates would be relatively significant. Since the paper has explored the VaR, a couple of hypotheses are presented because VaR has been widely used as a powerful tool for financial risk management. Then, VaR is used for measuring the agricultural risk as risk management, which is defined as factors that impact farming can cause swings in their incomes. If VaR allows non-financial firms to assess the potential losses to the portfolio, VaR shall allow farmers to assess the potential losses to the crop portfolio (Manfredo and Leuthord, 2001).

A perfectly competitive market has few features from the other markets: a large number of buyers and sellers, sellers produce homogenous goods and services, firms can freely enter and exit the market, and supply and demand both are price takers (Makowski and Ostroy, 2001). Although there are some drawbacks from these features, for instance, farmers do not have much influence on commodity prices as well as quantity of demand (Jensen et al., 2015).

The rest of the paper is organised as follows: in Section 2, the literature review is discussed in detail. In Section 3, the methodology is described. In Section 4, the results are presented. Finally, in Section 5, the conclusion and direction of future research are provided.

2 Literature review

The research aims to introduce some of the relevant studies that were conducted in the past. As mentioned above, a hand full of research studies were used to measure risk by utilising the VaR estimation. As a policy perspective, Nganje et al. (2006) studied Hazard Analysis and Critical Control Point (HACCP) upon the prediction of food safety losses in Turkey. The objective of this paper was to predict the food safety losses before HACCP in medium and large-scale turkey processors, after implementing augmented HACCP, and then determine the cost and benefits of augmented HACCP implementation in monetary term. They used a VaR approach to predict food safety losses. In this regard, VaR provides a framework for assisting firm management in assessing the food safety risks in monetary terms and evaluating economic incentives to implement HACCP. The contribution of the research was that VaR is sufficient to predict food safety loss by turkey processing plants. Food safety losses significantly declined following HACCP implementation. Medium and Large scale turkey processors are more likely to benefit from augmented HACCP than small scale turkey processors.

Wilson et al. (2007) had another exciting research, which used VaR. VaR procedure is applied for the bread baking company. The objective of the research is to apply VaR as a risk management tool in risk selling limits. VaR also complimented with management goals competition and conducted within the industry. The results show that VaR provides an intuitive measure of risk for decision-makers as the portfolio distribution is a non-normal distribution-based. VaR can be derived from a portfolio of inputs and measures of risk before its consequences are realised.

Manfredo and Leuthold (2001) had research upon the cattle feeding margin by utilising the VaR as well. The objective of the paper focuses on examination VaR measures in the context of cattle feeding margin. In addition to that, research also introduced alternative estimation techniques, both parametric and nonparametric. The paper concluded that "It is difficult to deem one measure to be the best." However, VaR appears to provide robust estimates for every three confidence levels test using a wide array of evaluation criteria.

Wilson et al. (2009) illustrated the risk and returned implication for malt barley production. They used a Monte-Carlo simulation model, and their results indicated that farmers encounter more financial risk without crop insurance or contract. Specifically, Multi-peril crop insurance lowers expected returns, however downside risk reduced as well.

Dahl et al. (2004) developed the research based on the application of HRSW. This research was interesting because it shows the trade-off between yields and characteristics valued by end-users. The statistics of this paper estimated the value of a new variety to end-users and growers by compared between traditional stochastic dominance and statistical test of stochastic dominance. The portfolio approach was to evaluate trade-off and risk among different varieties of HRSW. This research concluded that the stochastic dominance technique is an appropriate tool to compare and rank ex-ante values of varieties to growers and end-users separately and jointly under risk considerations. The result indicated that dominance varies depending on the grower, and the values of end-user are utilised. It is defined that risk is the probability of obtaining a crop yield, which is below a pre-specified threshold (Uddameri et al., 2020). Uddameri et al. (2020) assess a risk to evaluate crop yield loss risk by considering is as a function of corp water supply. The paper used a tiered risk assessment approach to provide a rational risk-based approach to see the impacts of crop water supply reduction.

Many research articles were published that measure risk associated with particular crops. However, most of the articles require to purchase in order to explore them. It limits the current research literature; however, this section includes a couple of literature that relatively crucial to the paper. The technological progress contributes to reducing the exposure to risk and downside risk in corn production even though this might affect the sites (Hammoudeh et al., 2013). Kim and Chavas (2003) addressed the role of the relative maturity of corn hybrids to manage risk. Hammer et al. (1996) mentioned that the average profit and loss from risk are estimated by evaluating a possible range of fixed and tactical strategies. Their results show that there is a significant increase in profit or reduction in risk, which were associated with adjustment of crop management.

Lastly, one research proved that risk is an essential role in corn, and soybean acreage decision is based on their empirical study. The result implication presented that cross-commodity allocates upon acreage can a suitable tool for the reduction of risk exposure (Chavas and Holt, 1989).

3 Methodology

3.1 Theoretical models

The paper hypothesises that if a farmer has a high fixed cost as business risk, then each net crop revenues are relatively small, and evaluation upon the downside risk would be helpful to farmers (Malfredo and Leuthold, 2001). Although higher risk will have higher net revenue or loss in general terms. This paper used two methods: VaR and stochastic dominance. Both methods are well known as powerful tools, and both are appropriate tools for measuring risk assessment. First, this paper explores the theoretical model for VaR and the second theoretical model for stochastic dominance. The last theoretical model focuses on copula. Since total input cost and total revenue considered as farm assets, this paper utilised the copula to capture the extreme values from each asset in the portfolio analysis.

This VaR conceptual framework is based on the framework explored in Malfredo and Leuthold (2001). VaR measures low probability events that exist in the lower tail of a distribution. Primarily, VaR constructed as $W = W_0 (1 + R)$ by Jorion and Khoury (1996) where W_0 the initial value of the portfolio and R is portfolio returns.

Hence, the general distribution of future portfolio value $F(W)$, Jorion and Khoury (1996) defines VaR as:

$$1 - c = \int_{-\infty}^{w^*} f(W)dw \tag{1}$$

where W^* is the end-of-period portfolio value when worst possible returns (R^*) occur, and c is a predetermined confidence level associated with W^*. By relating W^* with the predetermined confident level c. W^* should not be faced more than $1 - c\%$ of the time. Based on the direct function of portfolio returns, equation (1) could be written as replacing the W^* by $-|R^*|$. Because of the most scenario, the critical value of R^* would be negative in large sets of portfolios. If we are assuming the equation, 1 is the standard normal distribution $F(v)$ where $v \approx (0, 1)$, and R^* with the standard normal deviate (α) by normalising R^*-μ and setting

$$-\alpha = \frac{-|R^*| - \mu}{\sigma} \tag{2}$$

where μ is the mean return. Through equation (2), Jorion and Khoury (1996) subsequently shows that

$$1 - c = \int_{-\infty}^{w^*} f(W)dw = \int_{-\infty}^{-|R^*|} f(R)dR = \int_{-\infty}^{-\alpha} f(v)dv \tag{3}$$

It allows VaR to be represented in terms of critical portfolio value (W^*), critical returns (R^*), or normal deviate (α). Finally, VaR can be defined as:

$$VaR = W_o \alpha\sigma \tag{4}$$

where W_0 is initial portfolio value, (α) is the normal deviate associated with $1 - c$, and σ is the portfolio standard deviation. The important parametric of VaR in equation (4) is the estimate the portfolio standard deviation (σ), this is also preferred as portfolio volatility.

With the VaR method, this paper can predict with a certain level of confidence in potential portfolio losses (in this case portfolio of crop net revenue) in a given period due to adverse input total cost or total revenue movement in the asset of the portfolio. For instance, VaR estimated corn net revenue in South Valley region is 41 dollar per acre in the year of 2017 at the 95% confidence level implies that in South Valley region, corn net revenue losses should not exceed 41 dollars per acre more than 5% of the time in the year of 2017.

The stochastic dominance conceptual framework is based on Chavas (2004). The textbook title is *Risk Analysis in Theory and Practice*. Stochastic dominance allows the platform to rank or to compare choices among risky alternative strategies when preferences are not precisely known (Whitmore and Findlay, 1978).

Let us consider a decision-maker with a risk preference function $U(x)$, $L \leq x \leq M$, and encountering a choice between two risky prospects represented by the probability function $f(x)$ and $g(x)$. The associated distribution function is as follows:

$$F(x) = \int_L^x f(y)dy, \tag{5}$$

and

$$G(x) = \int_L^M g(y)dy, \tag{6}$$

Under the expected utility model, $f(x) \geq^* g(x)$ if and only if $E_f\, U(x) \geq E_g\, U(x)$, where E_f and E_g are expectation operators based on the probability function $f(x)$ and $g(x)$, respectively. Since $E_f\, U(x) - E_g\, U(x)$, $= \int_L^M U(x)[f(x) - g(x)]dx$, this can be written as

$$f(x) \geq^* g(x) \text{ if and only if } \int_L^M U(x)\left[f(x) - g(x)\right]dx \geq 0, \tag{7}$$

where $f(x) \geq^* g(x)$ means that the probability function $f(x)$ is preferred to $g(x)$.

Therefore, determining the sign of the term $\left[\int_L^M U(x)[f(x) - g(x)]dx\right]$ is a necessary and sufficient condition to decide that the probability function $f(x)$ is preferred to $g(x)$.

The purpose of stochastic dominance is to evaluate the sign of this expression with a minimum amount of information about the utility function $U(x)$. By using the stochastic dominance method, this paper could able to show which region is most dominant among regions and which region is less dominant among regions in ND.

Copulas are revealed to be a potent tool in the finance industry. This tool is used in modelling the different sorts of existing values in assets (Costinot et al., 2000). Copulas have been introduced by Sklar (1959) to the analysis of probabilistic metric spaces. Numerous statisticians have reviewed it in earliest. In this paper, copula can be explained simply.

Let us assume that a two-copula C is a bivariate uniform distribution. C is function from $[0, 1]^2$ to $[0, 1]$ with positive probability masses. The reason why all net revenues are uniform, thus,

$$C\left(1, u_2\right) = u_2 \tag{8a}$$

$$C\left(u_1, 1\right) = u_1 \tag{8b}$$

By construction, it becomes the function F defined by

$$F\left(x_1, x_2\right) = C\left(F_1\left(x_1\right), F_2\left(x_2\right)\right) \tag{9}$$

where F_n a univariate distribution is a bivariate probability distribution. Based on the definition F_1 and F_2 are two joint distributions. The purpose of using copula in this paper is to control extreme values and captures the correlation between two assets in three different crops. This analysis would critically important because the paper utilised VaR as the main estimation procedure for portfolio analysis. In other words, the results from VaR with copula is expected to be much robust.

Table 1 Descriptive data summary in farm input direct expense in each six region

Region	*South Valley*			*North Valley*			*South Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	$280.5	$118.0	$154.5	$248.2	$114.8	$154.4	$204.2	$116.2	$110.8
St. dev.	$76.5	$32.2	$44.4	$76.6	$33.7	$45.4	$60.9	$34.0	$36.4
Minimum	$152.3	$66.9	$78.7	$125.9	$69.4	$75.5	$107.9	$67.8	$55.9
Maximum	$380.8	$157.4	$209.5	$344.1	$159.3	$213.0	$293.5	$158.6	$159.3
Region	*North Central*			*North East*			*East Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	$194.7	$110.5	$120.8	$238.6	$131.0	$140.3	$235.7	$120.0	$134.9
St. dev.	$64.3	$31.2	$41.0	$75.3	$42.1	$45.9	$76.7	$34.2	$45.7
Minimum	$94.4	$63.9	$55.2	$117.7	$70.0	$65.3	$116.3	$71.6	$62.8
Maximum	$270.0	$147.0	$167.4	$329.1	$182.7	$195.4	$331.6	$161.0	$189.3

Table 2 Descriptive data summary in each three crop's yield in each six region (in thousand tons)

Region	*South Valley*			*North Valley*			*South Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	109.8	30.9	42.1	89.2	26.2	42.3	84.4	22.6	27.1
St. dev.	25.5	5.0	10.0	27.6	7.3	8.4	21.3	7.4	9.6
Minimum	49.3	15.4	16.1	40.5	13.0	22.5	44.1	8.0	5.5
Maximum	155.4	40.5	59.8	129.7	38.5	57.1	125.2	35.9	48.1
Region	*North Central*			*North East*			*East Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	70.5	21.9	29.4	77.3	22.3	34.0	85.3	25.7	34.4
St. dev.	21.1	7.2	7.2	28.7	7.9	8.4	28.4	7.7	8.4
Minimum	18.4	8.0	9.5	24.0	8.0	17.0	36.6	9.0	12.7
Maximum	103.8	37.1	43.8	135.6	40.8	54.9	131.6	37.7	48.5

Table 3 Descriptive data summary in each three crop's price in each six region

Region	*South Valley*			*North Valley*			*South Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	$3.4	$8.8	$5.1	$3.0	$8.4	$3.9	$2.9	$8.7	$5.2
St. dev.	$0.1	$0.5	$0.4	$0.2	$0.5	$0.6	$0.2	$0.5	$0.4
Minimum	$3.1	$7.7	$4.3	$2.3	$7.5	$2.9	$2.2	$7.7	$4.2
Maximum	$3.9	$9.8	$6.1	$3.6	$9.7	$5.6	$3.5	$9.6	$6.2
Region	*North Central*			*North East*			*East Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	$2.7	$8.4	$5.3	$3.1	$8.7	$5.1	$3.2	$8.4	$5.1
St. dev.	$0.3	$0.5	$0.5	$0.2	$0.5	$0.5	$0.2	$0.5	$0.5
Minimum	$2.2	$7.6	$4.4	$2.6	$7.6	$4.2	$2.8	$7.6	$4.2
Maximum	$3.2	$9.5	$6.6	$3.6	$9.6	$6.3	$3.8	$9.5	$6.2

Table 4 Descriptive data summary in each three crop's net returns in each six region

Region	*South Valley*			*North Valley*			*South Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	111.7	159.8	71.7	21.0	104.3	25.6	62.9	77.5	31.4
St. dev.	117.3	58.3	71.4	112.1	74.3	65.0	87.7	80.8	61.7
Minimum	−255.1	−126.0	−176.0	−248.8	−69.0	−147.3	−202.6	−106.3	−170.6
Maximum	429.6	317.8	285.4	440.3	308.5	227.3	311.4	276.7	259.2
Region	*North Central*			*North East*			*East Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
Mean	43.5	84.0	38.9	−14.0	60.9	50.7	26.7	117.3	60.2
St. dev.	89.8	66.1	54.3	103.4	77.5	64.8	113.4	74.7	66.1
Minimum	−234.9	−111.4	−192.3	−295.7	−189.5	−147.3	−255.9	−106.8	−136.2
Maximum	272.1	284.9	287.8	302.4	326.6	277.5	411.3	279.1	225.1

3.2 Empirical model

There are not many pieces of research that focus on the crop net revenue application by using VaR (Wilson and Dahl, 2014). One of the observations presented in this paper is a high fixed cost as a business risk. By evaluating the VaR measures in the context of three different crops grown in ND, it would help the insight for overall agriculture performance throughout the state of ND. However, the paper mainly concentrates net revenue of corn, soybean, and HRSW in selected six regions. Six regions are South Valley, North Valley, South Central, North Central, South East, and East Central. The explanation of these selected regions and specific reasons is in the data section.

Most importantly, these regions represent the majority of the agriculture of ND.

Crop net revenue's formula is expressed as:

$$\pi = TR - TC \tag{10}$$

where π = net revenue, TR = total revenue, and TC = total cost.

Unit measurement is: US dollars per acre, TC captures direct labour and management, and TR captures yield and commodity price. The total revenue defines as:

$$TR = Cyield * Cprice \tag{11}$$

where $Cyield$ = crop yield, and $Cprice$ = commodity market price.

As mention in the theory section, the essential parametric of VaR in equation (4) is the estimate the portfolio standard deviation (σ). This is also preferred as portfolio volatility.

For parametric VaR estimation, the variance of the crop net revenue (portfolio variance) is defined as:

$$\sigma_{pnr}^2 = w_{tr}^2\sigma_{tr}^2 + w_{tc}^2\sigma_{tc}^2 + 2w_{tr}w_{tc}\sigma_{tr}\sigma_{tc} + 2w_{tc}w_{tr}\rho_{tc,tr}\sigma_{tc}\sigma_{tr} \tag{12}$$

where σ_{tr}^2 and σ_{tc}^2 are the variances of total revenue and total costs, respectively. And $\rho_{tr,tc}$ and $\rho_{tc,tr}$ are the respective correlation between total revenue and total cost. The portfolio weights are w_{tr}^2 and w_{tc}^2. VaR is used for two main reasons: portfolio application and forecasting approach. Therefore, equation (12) is in forecasting framework with portfolio application, such that the individual variances (volatility) are correlation coefficient are forecasted, as VaR at any given annual t is:

$$VaR_{pnr,t} = \alpha\hat{\sigma}_{pnr.t+1} \tag{13}$$

where $\hat{\sigma}_{pnr.t+1}$ the portfolio volatility is the forecast of the crop net revenue, and α is the scale factor that corresponds to the desired confidence level. This paper uses two software: @RISK 7, and Simetar and both software are assessable to the Commodity Trading Room (CTR) at North Dakota State University.

3.2.1 VaR procedure steps, including copula

This paper takes the steps of the VaR procedure as following steps; first step: extract each different crop data, which includes annual yield, commodity spot price, and total direct cost. Second step: using the batch fit method to estimate best fit data distribution for all raw data with 5,000 iterations. Third step: extract 5,000 iterations from the simulated dataset. The fourth step: uses equation (11) to derive total revenue from 5,000 iterations for yield and spot price. Fifth step: use the batch fit method to estimate best fit data distribution and function for total revenue and total cost. Sixth step: to fit copula under define correlations function to generate the copula matrix. Seventh step: extract 5,000 iterations from the simulated dataset with copula captured. Eight step: use equation (10) to derive the net revenue from total revenue and total cost. Ninth step: calculate the difference of net revenue by current year minus last year. Tenth step: forecast net revenue by current year's net revenue plus (current year difference plus last year difference divided by two). Eleventh step: use the batch fit method to use best fit data distribution and function for forecasted net revenue. Lasts step: add output upon the forecasted net revenue function cell to simulate 5,000 iterations. It gives the forecasted net revenue of VaR measurement for net crop revenue. These 12 steps occurred 18 times, because of six regions multiplied by three different crops.

3.2.2 Stochastic dominance procedure steps

Stochastic dominance procedure steps are relatively shorter since this method is used after the VaR procedure. Thus, steps follow as the first step: extract all the forecasted net revenues for each region and sorts by the different crops. Second step: use the stochastic dominance function to estimate the stochastic dominance concerning a function, stoplight analysis, and cumulative distribution function for every six regions under a single crop. Last step: repeat the same steps two more times to estimates the remaining other two crops.

3.3 Data sources and descriptive statistics

This paper uses daily closing spot prices for the three different commodities corn, soybean, and HRSW. Each region has a different closing spot price for one commodity; this means each commodity has different closing prices for six different regions. The period of closing spot prices collected from 31 November 2014 to 30 November 2015. The closing spot prices are collected from the DTN computer software that is accessible from CTR. Besides, the paper also uses annual crop yield data for every three crops for six different regions. The crop yield data is extracted from USDA-NASS by county level for the period from the year 1982 to the year 2014. Lastly, direct cost data is collected from the crop budgeting report, and the time period is from 2004 to 2016. The direct cost data are accessible from the NDSU farm management website. The paper focuses on forecasting downside risk associated with each net crop revenue in selected six different ND regions.

The details of the six different regions are North Valley, South Valley, East Central, South Central, North Central, and North East. The six different counties represent each region, and each county is included in the six regions, which means that six counties are selected for each region. For instance, Walsh County represents the North Valley region, Stutsman County represents the East Central region, Richland County represents South Valley region, Emmons County represents the South Central region, McHenry County represents the North Central region, and Ramsey County represents North East region. The data sources, such as spot prices, crop yield, and operation expenses in each of the three crops were available.

The HRSW production in ND is ranked as number 1 in the nation, which accounts for about 37% of the nation's all HRSW. Soybean production in ND is ranked number 10, which takes about 4%. Corn production in ND is ranked number 12. Descriptive data summaries are present in Tables 1, 2, 3, and 4. Tables 1, 2, and 3 show the descriptive statistics of input variables (direct farm expenses, crop yields, and commodity market prices). Table 4 presents the descriptive statistics of the output variable (net return).

3.3.1 Evaluation

To test prediction accuracy and robustness of VaR results, Manfredo and Leuthold (2001) utilised two critical tests: likelihood ratio (LR) statistic and Z statistic for out-of-sampling basis. They estimated the number of violations based on the VaR estimates. For instance, "actual portfolio losses over the desired horizon exceeds the VaR estimates made for that particular period; a violation occurs." Therefore, if violations are in enough to that implied by a particular confidence level, the VaR measure is considered inadequate in measuring significant losses of the crop net revenue. This paper follows the same procedure to utilise the Z statistic to test VaR estimates are overestimated or underestimated. Also, the paper follows the same procedure to utilise the LR statistic to test the robustness of VaR estimate. The null hypothesis is $\delta = \delta^*$, where δ is the desired coverage level (5%) corresponding to the given confidence level (95%). δ^* is X/N, where X is the number of the recognised violations and N is a number of sample observations. Both testing methods are well explained in Malfredo and Leuthold (2001) research paper.

4 Results

Table 5 represents the VaR results for all six regions, including three different crops. The results are referring to the prediction for downside risk in three crops grown in ND.

Table 5 VaR results on each crop's net return in six regions with Z and LR test results

	South Valley			*North Valley*			*South Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
VaR	–25.8	80.1	–12.5	–41.2	–16.0	–41.0	–108.4	19.0	–48.9
Z test	0.2	–1.2	0.1	–1.3	–0.3	0.3	–0.6	–2.2	0.6
LR test	0.5	29.9	0.5	37.2	2.1	2.2	8.0	92.2	8.9
	North Central			*North East*			*East Central*		
	Corn	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*	*Corn*	*Soybean*	*Wheat*
VaR	–62.8	–0.2	–25.2	–137.6	–29.9	–24.5	–103.6	24.7	–17.5
Z test	0.6	–0.9	–0.3	–0.3	1.0	0.0	–0.6	–0.9	0.0
LR test	8.9	17.4	2.1	2.1	28.2	0.0	8.0	17.3	0.0

The interpretations are as follows. As the most considerable annual loss in North Valley region in the year of 2017, corn is predicted to be $–41.21 per acre, soybean is predicted to be $–16.02 per acre, and HRSW is predicted to be $–41.00 per acre. For the North Central region in the year 2017, corn is predicted to be $–62.75 per acre, soybean is predicted to be $–0.24 per acre, and HRSW is predicted to be $-25.21 per acre. For the

North East region, corn is predicted to be $–137.60 per acre, soybean is predicted to be $–29.88 per acre, and HRSW is predicted to be $–24.48 per acre. For the South Valley region, corn is predicted to be $–25.77 per acre, soybean is predicted to be $80.06 per acre, and HRSW is predicted to be $–12.49 per acre. For the South Central region in the year of 2017, corn is predicted to be $–108.41 per acre, soybean is predicted to be $19.04 per acre, and HRSW is predicted to be $–48.91 per acre. Lastly, for the East Central region in the year of 2017, corn is predicted to be $–103.64 per acre, soybean is predicted to be $24.73 per acre, and HRSW is predicted to be $–17.49 per acre. The critical Z value is 1.96 for a 5% significant level. The chi-squared critical value is 3.84 for a 5% significant level. Each VaR values are tested by the Z test as well as the LR test. Z-test results indicated all VaR values are neither overestimated nor underestimated because it is failed to reject the null hypothesis, and Z-test values are not higher than the critical value of 1.96 for 5% significant level. LR test indicated that following VaR values are robust: corn for North East and South Valley, soybean for North Valley, HRSW for North Valley, North Central, North East, South Valley, and East Central.

Table 6 Ranking performance among six regions in ND

Ranking among six regions						
	Corn	*Region*	*Soybean*	*Region*	*Wheat*	*Region*
Largest loss	–137.6	North East	–29.9	North East	–48.9	South Central
Least loss	–25.8	South Valley	80.1	South Valley	–12.5	South Valley
Ranking among the Northern Regions						
	Corn	*Region*	*Soybean*	*Region*	*Wheat*	*Region*
Largest loss	–137.6	North East	–29.9	North East	–41.0	North Valley
Least loss	–41.2	North Valley	–0.2	North Central	–24.5	North East
Ranking among South and Eastern Regions						
	Corn	*Region*	*Soybean*	*Region*	*Wheat*	*Region*
Largest loss	–108.4	South Central	19.0	South Central	–48.9	South Central
Least loss	–25.8	South Valley	80.1	South Valley	–12.5	South Valley

Table 6 represents the ranking performance. Each region is ranked by the most significant loss per acre and least loss per acre. North East has the highest downside risk for the commodity of corn and soybean in overall all regions ranking, and South Central has the highest downside risk for the commodity of HRSW. South Valley has the lowest downside risk for all three commodities. In the ranks among the northern regions is led by the North Central region, which has the highest downside risk for the commodity of corn and soybean as well. North Valley has the highest downside risk for the commodity of HRSW. However, North Valley has the lowest downside risk for the commodity of corn. North Central has the lowest downside risk for the commodity of soybean. North East has the lowest downside risk for the commodity of HRSW. Ranks among the south and east regions explained South Central has the highest downside risk for all three commodities. South Valley has the lowest downside risk for all three commodities.

Table 7 represents stochastic dominance results. This result is based on the analysis of the stochastic dominance with respect to a function (SDRF). The risk-averse coefficient is zero, which means each region is assumed to be the risk-neutral position. Based on these results, the paper would be able to generalise the SDRF measures and determine the difference between these six regions risk distributions. Among the six regions' net revenue distributions, the South Valley region is the most preferred because South Valley region has the lowest risk associated with a net return from corn, soybean, and HRSW. The North East region is the least preferred region for the commodity of corn and soybean. North Valley region is the least preferred region for the commodity of HRSW. The stochastic dominance analysis outcome has a likely result that South Valley has the lowest downside risk and most preferred region for grow commodity of corn, soybean, and HRSW. Moreover, we indicated that the North East has the highest downside risk and least preferred regions for grow commodity of corn and soybean. Lastly, it indicated that the VaR rank of northern regions that North Valley has the highest downside risk and least preferred regions concerning the commodity of HRSW.

Table 7 Stochastic dominance results in six regions based on the each three crop

Efficient set based on SDRF at lower RAC equals zero								
Corn			*Soybean*			*Wheat*		
Rank	*Region*	*Preference*	*Rank*	*Region*	*Preference*	*Rank*	*Region*	*Preference*
1	South Valley	Most preferred	1	South Valley	Most preferred	1	South Valley	Most preferred
2	South Central	2nd most	2	East Central	2nd most	2	East Central	2nd most
3	North Central	3rd most	3	North Valley	3rd most	3	North East	3rd most
4	East Central	4th most	4	North Central	4th most	4	North Central	4th most
5	North Valley	5th most	5	South Central	5th most	5	South Central	5th most
6	North East	Least preferred	6	North East	Least preferred	6	North Valley	Least preferred

5 Conclusions

Overall, the objective of this paper is to investigate the downside risk by utilising the VaR in the context of selected three different commodities. Based on the results, paper discovers the downside risk for three different commodities grown in six different regions in ND (see Table 3). The objective of this paper is to give an insight into setting risk limits for a local farmer who grows corn, soybean, and HRSW in the selected regions. Besides, these results would help the farmer to mitigate risk by analysing the risky commodities among these three. Lastly, these results demonstrate the downside risk as numeric values, so farmers could quickly analyse their investment strategy between every three commodities. Recently, farmers encountered with high fixed cost (business risk), the uncertainty of commodity output price, and uncertainty of demand volume. Thus, the paper developed three main contributions that would help farm more stable under the current condition of the market. First, understanding of risk exposure from different commodities is essential to choose which crop to grow. Second, the projection of net cash flow from each crop. Third, it assists better information for farmers to stabilise their revenue as well as net revenues from each crop.

The hypothesis of the paper highlights the high fixed cost as the business risk would be indicated by proxy of small net revenue as well as significant Var estimated value. The paper results confidently proved that some of the VaR values are relatively significant value concerning dollars per acre. For instance, the high downside risk for corn applies to regions such as the North East, East Central, and South Central. Huge downside risk for soybean applies to South Valley, and high downside risk for HRSW applies to North Valley and South Central. In the literature, most of the research paper concludes that VaR and stochastic dominance approach are appropriate methods to apply for risk management. The findings of this paper well prove these conclusions. A sufficient understanding of how the VaR and stochastic dominance could assist not only financial institutes or a multinational corporation, also it would be beneficial to farmers and ranchers to make smart decisions daily. Var and stochastic dominance methodology provide a generic interdisciplinary approach that can be integrated with the concepts of probability and statistics in the field of crop risk modelling to measure risk associated with crop yield in a sophisticated fashion. While this methodology can be adapted to any type of crop in a different region, the element of Var and stochastic dominance must be tailored to capture constraints of crop growth.

Furthermore, there are many potentials to explore this research. From a policy perspective, the paper can explore how the risk associated with different crops will impact on business risk as a whole comparison between VaR prediction of downside risk for a different crop before Farm Bill 179 and after. Lastly, VaR and stochastic dominance are practical and efficient tools for predicting and rank.

References

Chavas, J.P. (2004) *Risk Analysis in Theory and Practice*, Elsevier.

Chavas, J.P. and Holt, M.T. (1989) 'Acreage decisions under risk: the case of corn and soybeans', *American Journal of Agricultural Economics*, Vol. 72, No. 3, pp.529–538.

Collins, R.A. (1985) 'Expected utility, debt-equity structure, and risk balancing', *American Journal of Agricultural Economics*, Vol. 67, No. 3, pp.627–629.

Costinot, A., Roncalli, T. and Teiletche, J. (2000) *Revisiting the Dependence between Financial Markets with Copulas*, SSRN: 1032535.

Dahl, B.L., Wilson, W.W. and Nganje, W. (2004) 'Stochastic dominance in wheat variety development and release strategies', *Journal of Agricultural and Resource Economics*, Vol. 29, No. 1, pp.94–111.

Deaton, A. and Laroque, G. (1992) 'On the behaviour of commodity prices', *The Review of Economic Studies*, Vol. 59, No. 1, pp.1–23.

Gabriel, S.C. and Baker, C.B. (1980) 'Concepts of business and financial risk', *American Journal of Agricultural Economics*, Vol. 62, No. 3, pp.560–564.

Hammer, G.L., Holzworth, D.P. and Stone, R. (1996) 'The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability', *Crop and Pasture Science*, Vol. 47, No. 5, pp.717–737.

Hammoudeh, S., Santos, P.A. and Al-Hassan, A. (2013) 'Downside risk management and VaR based optimal portfolios for precious metals, oil and stocks', *The North American Journal of Economics and Finance*, Vol. 25, pp.318–334.

Jensen, F., Frost, H., Thøgersen, T., Andersen, P. and Andersen, J.L. (2015) 'Game theory and fish wars: the case of the Northeast Atlantic mackerel fishery', *Fisheries Research*, Vol. 172, pp.7–16.

Jorion, P. and Khoury, S. (1996) *Financial Risk Management*, Cambridge/Massachusetts.

Kim, K. and Chavas, J.P. (2003) 'Technological change and risk management: an application to the economics of corn production', *Agricultural Economics*, Vol. 29, No. 2, pp.125–142.

Makowski, L. and Ostroy, J.M. (2001) 'Perfect competition and the creativity of the market', *Journal of Economic Literature*, Vol. 39, No. 2, pp.479–535.

Manfredo, M.R. and Leuthold, R.M. (2001) 'Market risk and the cattle feeding margin: an application of value-at-risk', *Agribusiness*, Vol. 17, No. 3, pp.333–353.

Nganje, W.E., Siaplay, M., Kaitibie, S. and Acquah, E.T. (2006) 'Predicting food safety losses in turkey processing and the economic incentives of hazard analysis and critical control point (HACCP) intervention', *Agribusiness*, Vol. 22, No. 4, pp.475–489.

Sklar, M. (1959) *Fonctionsderépartitionà n dimensions etleursmarges*, Publ. Inst. Statist. Univ. Paris, Vol. 8, pp.229–231.

Uddameri, V., Ghaseminejad, A. and Hernandez, E.A. (2020) 'A tiered stochastic framework for assessing crop yield loss risks due to water scarcity under different uncertainty levels', *Agricultural Water Management*, Vol. 238, p.106226.

Whitmore, G.A. and Findlay, M.C. (1978) *Stochastic Dominance: An Approach to Decision-Making under Risk*, January, Lexington Books.

Wilson, W., Gustafson, C. and Dahl, B. (2009) 'Crop insurance in malting barley: a stochastic dominance analysis', *Agricultural Finance Review*, Vol. 69, No. 1, pp.98–112.

Wilson, W.W. and Dahl, B. (2014) 'Contracting for canola in the great plains states', *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, Vol. 62, No. 1, pp.89–106.

Wilson, W.W. and Miljkovic, D. (2013) 'Dynamic interrelationships in hard wheat basis markets', *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, Vol. 61, No. 3, pp.397–416

Wilson, W.W., Nganje, W.E. and Hawes, C.R. (2007) 'Value-at-risk in bakery procurement', *Applied Economic Perspectives and Policy*, Vol. 29, No. 3, pp.581–595.