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Full Length Research paper

Recognizing Production Risk a Use of Best-worst Scaling in Agriculture

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A Reducing agricultural revenue variability is mostly dependent on risk assessment and management. The perceived significance of the risk and the perceived degree of control that producers have over risk management are two variables that may influence the selection of risk management instruments and techniques. This study examines how Saskatchewan grain and oilseed farmers perceive the most significant sources of risk and the factors that affect these perceptions using data from a 2017 survey. It does this by using a count-based method of best-worst scaling and latent class cluster analysis. The findings imply that the most significant risks for farmers are those related to production and marketing, including fluctuations in input pricing, rainfall variability, and output price variation. Nevertheless, the findings also show variation in how these hazards were responded to, indicating that farmers must handle risk in a variety of ways.

Key words: Risk, Risk management, Best-worst scaling, Latent class cluster.

INTRODUCTION

It In their farming operations, farmers must contend with fluctuating input and product prices, erratic weather patterns, and technological advancements. Production, marketing, financial, and institutional risk are all impacted by changes in input and output markets (Guerin and Guerin, 1994). If these risks are not appropriately recognized and controlled, farm revenue may fluctuate significantly. Although producers understand the fundamental causes of these risks (Hwang et al., 2016; Lei et al., 2013; Oerke, 2006; Savary et al., 2012), farmers must occasionally pay hefty prices to try to prevent or lessen the occurrences that cause fluctuations in farm income (Beckie et al., 1999). As a result, farmers may decide to control hazards over which they have more control or those they believe are more crucial to farm success.

According to Hansson and Lagerkvist (2012), "farmers' risk preferences may be more associated with their personal characteristics." According to Sherrick et al. (2004) and Velandia et al. (2009), for instance, farmers' risk choices are significantly influenced by farm or farmer characteristics like age, farm size, risk perception, debt to asset ratio, off-farm income, and education. The perceived ability of a farmer to completely or partially eliminate or mitigate the risk may also have an impact on variations in how risk is perceived. According to research by Shapira (1986) and MacCrimmon and Wehrung (1986), the majority of managers think that risk is controlled and manageable and that risk uncertainty is not caused by external factors. As a result, managers may disregard risk assessments and concentrate on obtaining fresh data that is required for implementing changes to lower uncertainty (March and Shapira, 1987). This implies that managers' perceptions of their degree of control over marketing and production results may affect how they perceive and need to manage the risks associated with their farm business.

This study aims to investigate how Canadian producers' perceptions of risk are influenced by farm and managerial attributes. We use latent class clustering and best-worst scaling (BWS) techniques to investigate the relationship between risk perceptions and farm and managerial characteristics using data from a 2017 survey of Saskatchewan producers. The best-worst questions were created using a total of sixteen risk variables that covered marketing, production, financial, institutional, and personal sources. Additionally, a latent class cluster analysis is used to further investigate the heterogeneity in producer responses. Rotter's (1966) internal-external locus of control measure is used to analyze managerial variations and how a farmer's view of their capacity to manage risks influences the significance of various risk sources. We would anticipate that internal managers—those who believe that their own actions, rather than external sources, greatly influence outcomes—would have a different perspective on the sources of risk than external managers, in keeping with the findings of Miller et al. (1982).

A recent study by Thompson et al. (2019) looked at how American farmers rank various risk management categories, including marketing, production, finance, human resources, and law. They discovered that the most significant risk was thought to be production risk, which was followed by financial and marketing risks. Although Thompson et al. (2019) have shed much-needed light on the broad risk categories that matter to producers, it is still unclear how producers rank the different risk sources that fall under these categories. For instance, variations in rainfall, other natural calamities like hail or flooding, or the existence of pests and diseases that could impact agricultural yield could all contribute to production unpredictability. Furthermore, depending on the manager's capacity to control the risk and willingness to assume it, personal characteristics like locus of control and risk attitude may also affect how important they believe the sources of risk to be. Although perceived risks may vary from place to place and from farm to farm, policymakers and extension staff may be better able to create appropriate policy tools and dissemination strategies if they have a better understanding of the main sources of risk. This way, producers can find the right tool to fit their own risk profile.

Our findings, which were obtained via a count-based BWS technique, indicate that respondents are more worried about risk factors that directly affect farm income. Two separate groups appear when respondents are grouped according to latent class clusters. The first group consists of managers who give more weight to business and financial risks, such as the cost of inputs and products and the usage of financial leverage. The managers in the other cluster are more concerned with risk variables that affect quality and yield. Our findings also demonstrate that producers agreed on the significance of risks such fluctuating rainfall and input price fluctuations. Respondents vary somewhat in how they evaluate the significance of the risks other than production, marketing, and financial concerns.

This is how the rest of the paper is organized. We begin by giving a quick overview of the research on risk perception in agriculture and setting the scene for our study. We then describe our experimental setup and the data collection techniques we employed for the study. Next, we look at the outcomes of the latent class cluster analysis and the BWS. We examine the managerial implications of our findings as we wrap up the article.

Farmers' perception of risk

Uncertainties about the weather, prices, government regulations, international markets, and other factors can all be causes of risk in farming. Variations in farm revenues and input costs, and consequently, farm income, may result from these uncertainties. Sources of risk that impact commercial farm operations' performance have been extensively studied (Antón et al., 2011; Chavas and Shi, 2015; Harwood et al., 1999; Thompson et al., 2019). However, the creation and acceptance of risk management solutions in production are influenced by the perception of the specific hazards that each farmer faces. The significance of these perceived hazards may vary across farmers and among particular crop kinds.

In addition to rising operating expenses, poor margins, and high fixed costs, farmers in Saskatchewan face a variety of production and economic risks, including drought, excessive moisture, frost, hail, pests, and diseases (Howden, 2016). All of these have the potential to affect farm income and jeopardize the farm business's long-term survival. This is not to imply that Saskatchewanian producers face a unique set of risk factors.

Producers in Saskatchewan face higher levels of trade and policy risk in specific markets (such as those for canola, lentils, and chickpeas) in addition to production and financial concerns. Since a large portion of production is exported, institutional risks including modifications to national, regional, and global trade laws can affect both farm-gate prices and production choices. For instance, limiting imports through tariffs and quotas might have a detrimental impact on exporters' access to markets, change the choices made by producers of grains and oilseeds, or lower domestic prices. The Indian government's recent hike in tariffs on Canadian peas, lentils, and chickpeas serves as one example (Cowan, 2018). While planted acres for other crops have been largely consistent, these disruptions occur at a time when canola and lentil production and seeded acres have been rising. Exports of canola seed, non-durum wheat, canola oil, and two significant pulse crops increased between 2013 and 2016 (Government of Saskatchewan, 2016), according to statistics on area, output, and exports (Table 1).

Risk factors for farmers include yield and price volatility, which have a significant impact on farm income. Farmers view yield and price volatility as the main sources of risk to their farm business, according to surveys of wheat and maize farmers conducted in the US and Australia (Harwood et al., 1999; Kimura et al., 2010; Knutson et al., 1998). The significance of these hazards may differ in other jurisdictions with distinct policy contexts. For instance, Swiss crop producers stated that price and yield hazards were significant sources of risk for them, while costs had little bearing on income variability (El Benni and Finger, 2012). This could indicate that respondents place greater importance on business risks and how they affect the farm's financial health. According to Gabriel and Baker (1980), the level of business risks present on a farm affects a company's financial risk. In other words, more business risk increases the firm's net cash flow's fluctuation. According to Gabriel and Baker (1980), there is a trade-off between business risk and financial risk, and a decrease in business risk would result in a higher level of financial risk being accepted. Additionally, Table 1 revealed the usual business hazards. Saskatchewan's principal grain and oilseed crops' estimated acreage, productivity, and export volume

(Statistics Canada, 2017).

According to the research, farmers are also concerned about the risk of pests and diseases, changes in the climate and weather, input costs, and institutional variables. Crop farmers in Alabama and Florida cite rainfall variability, pests (insects, weeds, and illnesses), and operating input costs as their top sources of risk, according to a study by Boggess et al. (1985) on the causes of farm risk and farm managers' reactions to it. In certain states in the United States, small grain producers and mixed farmers identify pests and diseases as the biggest threats to their output. Cotton farmers, on the other hand, regard input cost unpredictability as their biggest source of risk (Patrick et al., 1985).

Changes in the political and economic climate are among the main risk worries of rice farmers in Argentina, another nation that exports a significant portion of its output (Pellegrino, 1999). Crop prices, yield volatility, and institutional concerns were cited as the main sources of risk by Norwegian conventional and organic cash crop farmers (Koesling et al., 2004). on Australia, farmers on the Upper Eyre Peninsula of South Australia and Southwest Queensland identified climate unpredictability as one of their top risk concerns; however, government policy was also a major source of risk for those in Southwest Queensland (Nguyen et al., 2005). According to Peterson and Kastens (2006), organic grain farmers in the United States also take into account risks from weather, weeds, insects, and deer, as well as institutional factors like the USDA standards' lack of severity and the industry participants' failure to enforce the organic standards. According to Peterson and Kastens (2006), farmers did not view marketing concerns like low pricing and non-fulfilled contracts as significant risk factors.

These studies show that while there is some uniformity in the hazards that farmers encounter, there is also variation in the sources of risk that farmers perceive based on the type of farm, the product that is produced, and the farm's location. According to Antón et al. (2011), farmers' attitudes about risk change depending on their exposure and level of experience. The authors identified three distinct risk levels and recommended that farmers assume responsibility for addressing some common or typical risks. Furthermore, the majority of research have employed conventional scaling techniques (such Likert scales) to comprehend farmers' perceptions of risk; in contrast, the current study uses BWS techniques, which is an alternative tool for examining the relative relevance of qualities.

Experimental design

A study of grain and oilseed farmers in Saskatchewan was conducted to find out how important they thought the different sources of risk to a farm business were. In the survey, participants were asked about their farm business, risk tolerance, and how much control they believe they have over the variables that impact farm performance. According to Ochieng and Hobbs (2016), locus of control examines whether farmers believe that their ability to control risk is based on their own skills and efforts (internal locus of control) or on outside factors (external locus of control), over which they have little to no control. By asking producers to choose the "best" and "worst" of a number of scenarios, we employ a BWS experimental design to investigate their perceptions of the relative relevance of the various sources of hazards, much as Thompson et al. (2019). Nevertheless, we utilize a count-based strategy since our design uses the count-based strategy for Case 1 design (which is comparable to the strategy outlined in Louviere et al. (2013) and utilized in Ochieng and Hobbs (2016)). The design and implementation of the BWS in this study are explained in this section.

Louviere and Woodworth (1991) created the best-worst technique, which was originally published in 1992 (Finn and Louviere, 1992). According to Augger et al. (2007), the best-worst technique presupposes an underlying subjective dimension, such as degree of importance or degree of interest, and uses this dimension to measure the placement of a set of objects. According to the current study, the objects are the different kinds of risk that farmers deem significant, and the underlying dimension is the degree of relevance. Respondents can choose the "best" and "worst" qualities (sources of risk according to this study) from a repeating number of choice sets using the stated preference approach. To maximize the difference between two items on an underlying scale of significance, respondents are presented with a chosen set of options (Erdem and Rigby, 2013). Each scenario's best and worst options are tallied, converted into a best-worst score, and the score's data is utilized to calculate each attribute's relative relevance in the decision sets by counting how many times it is chosen as the "best" or "worst."

The BWS approach reduces the likelihood of inconsistencies in responses related to ratings or rankings and ranks a large number of things according to their significance to an individual (Erdem et al., 2012). When respondents are given lengthy lists of items to rank or rate, this is particularly crucial (Erdem and Rigby, 2013). The study's decision to use BWS methods was driven by an evaluation of the numerous drawbacks of the alternative approaches as well as the relative benefits of the BWS approach, which outperforms other measuring techniques like paired comparisons and category rating scales. Since the rating approach requires respondents to make a discriminating decision among the concerns being considered, Auger et al. (2007) suggest that BWS could help address the issues related to the usage of rating in terms of revealing the genuine preferences of respondents. In examining consumer preferences for food labeling features, Lagerkvist (2013) also contrasted BWS and direct ranking. He found that BWS produces more consistent dominant ordering of attributes importance and enhances individual choice predictions when compared to direct ranking. Thompson et al. (2019) recently investigated American farmers' perceptions of traditional sources of risk (production, marketing, and financing) using BWS and latent class modeling. According to their findings, conventional risk sources were more significant to their sample of producers than legal or human risk sources.
It is crucial to make sure that all identified items are included in the option sets and that potential comparisons are presented an equal number of times when designing a survey that will use BWS (Louviere & Woodworth, 1991). Additionally, it was recommended by Vermunt and Magidson (2014) that item combinations be

carefully planned to ensure that each item and pair of things is displayed an equal number of times. Each feature is orthogonal and appears an equal number of times thanks to the 2K factorial design (Coltman et al., 2011).

Sixteen risk factors that were found through a literature study were subjected to the design. 16 decision sets for the "sources of risk" were produced as a result. The survey's best-worst section was constructed with four items in each option set, and each source of risk was matched once and featured four times across all choice sets. Respondents were asked to choose the sources of hazards they believed were significant for their agricultural business in a set of sixteen repeated-choice questions. Since we are interested in the relative ratings of the risk sources, this design reflects a Case 1 BWS method (Dumbrell et al., 2016; Louviere et al., 2013). An example of a Case 1 decision set is shown in Table 2.

Data collection

Data was gathered via an online poll of grain and oilseed producers in Saskatchewan. Respondents to the survey were selected from Insightrix® Research, Inc.'s (Saskatoon, SK, Canada) producer database. To make sure the participants were producers of grains or oilseeds and that they were heavily involved in farm operations decision-making, two screening questions were employed. The poll received responses from 600 farmers who grow grains and oilseeds. To prevent respondent identification, maintain anonymity, and avoid duplicate responses, each participant was given a unique identification code. The responses that were kept made up the data set after these response validity checks. The average age of the respondents was 53, as indicated in Table 3, which is marginally younger than the average age of Saskatchewan farm operators, which was 55 in the 2016 Census of Agriculture, according to Statistics Canada (Statistics Canada, 2016). About 39.8% of the participants had a high school, vocational, or technical education, 23.7% had a college degree, 28.2% had a university degree, and roughly 7.7% had a graduate degree. The majority of participants (77.2%) were men. The majority of those surveyed (55%) had been farmers for more than 31 years. Based on gross sales below CAN$500,000, the majority of respondents might be categorized as small to medium-sized businesses. Sales of CAN$ 1 million or more were reported by nearly one-fifth of respondents (18.5%).

Data analysis

The number of times a risk source was chosen as least important was deducted from the number of times it was chosen as most important for each of the sixteen risk sources in order to ascertain farmers' perceptions of their most significant risk factors. Case 1: In order to rank the individual attributes, BWS often use the traditional procedure of calculating best minus worst scores for each attribute (Adamsen et al., 2013; Flynn, 2010; Louviere et al., 2013). We use the count method, which has been used by other authors to analyze Case 1 best-worst data (Adamsen et al., 2013; Goodman et al., 2005; Ochieng and Hobbs, 2016), even though more sophisticated techniques, like Maximum Likelihood Estimation of multinomial logit models, have previously been used for Case 1 models (Thompson et al., 2019). The difference between all best and worst counts was divided by the total number of respondents to provide BWS at the aggregate level for each item in order to calculate the relative importance of the risk sources overall. Equation 1 was used to convert the best-worst ratings into standard scores in accordance with Ochieng and Hobbs (2016).

where *n* is the number of survey respondents and 4 is the frequency with which each source of risk appears in the design.

Goodman et al. (2005) claim that standardization facilitates comparisons between various respondent groups. Ratio scores were created since the aggregate standard scores don't reveal the proportional relevance of the features. In order to compare the relative relevance of qualities (risk sources), the ratio scores standardize the best-worst values. Equation 2 was used to determine the ratio scores in accordance with Loose and Lockshin (2013).

Case 1 best-worst measurement does not reveal individual differences that may be present in the data, therefore, the standard deviation of individual best-worst scores was calculated to understand whether farmers are homogenous with their choices (Mueller and Rungie, 2009). A standard deviation above one provides suggests heterogeneity in the responses of producers (Mueller and Rungie, 2009).

Best-worst scaling results: the relative importance of the sources of risk

Table 4 lists each risk source's ranking and significance according to the BWS standard score. The two most significant risk factors among all respondents are "variations in product prices" and "rainfall variability," which are followed by: (3) changes in input prices; (4) pests and diseases; (5) accidents and health/disability; (6) natural disasters; and (7) inability to meet quality requirements.

Only a basic ranking of the risk sources is provided by the standard score ranking; it offers little insight into the relative importance of these hazards. Equation 2 was used to estimate a probability ratio or interval scale from the best-worst scores in order to comprehend the relative relevance. The ranking according to the ratio score (a measure of relative relevance) is displayed in Column 11 of Table 4. Since "change in product prices" is the risk with the highest ranking interval, we rescaled it to match 100. There was little change in the ranking of the most significant risk factors according to the standardized square root interval scale, which indicates the relative relevance of the qualities. The normal score ranking and the top five hazards were identical. The top risk was remained "changes in product prices," which were followed by: (2) variability in rainfall; (3) price changes for inputs; (4) pests and diseases; and (5) accidents and health/disability. According to the standardized square root interval scale used for ranking, "rainfall variability" and "change in input prices" are 0.73 and 0.62 times more significant than "changes in product prices," which producers view as the most significant factor. The findings also show a significant gap between the primary risk (ranked first) and the other risk sources that producers deem significant. This indicates that, in comparison to the other risks, "changes in product prices" are the most significant risk. Although to a lesser extent, the hazards that came in second through fourth place were also very significant.

Overall, the findings indicate that Saskatchewan grain and oilseed producers place greater value on input and marketing-related production and pricing risks than on personal and health hazards. The elements of the farm that farmers have less influence over, such rainfall and product pricing, were linked to many of the higher risk ratings. This would imply that threats that impact the farm's financial stability are of greater concern to the respondents. For instance, the amount of output that may be sold or the money made from the sale of output are adversely affected by large yield losses brought on by weather-related factors like excessive or limited rainfall, natural catastrophes, and decreased pricing. Price increases for inputs have the potential to drastically raise manufacturing costs, lower profit margins, and negatively affect net cash flow. Furthermore, the fact that producers have little influence over business risks and that their activities don't significantly reduce them may help to explain why they are so important to them. The outcome aligns with previous research that has revealed that farmers place a higher value on business risk than other risks (El Benni and Finger, 2012; Kimura et al., 2010; Thompson et al., 2019).

As previously mentioned, because Case 1 best-worst measurements only provide data on the overall ranking of the hazards, they are unable to identify any individual differences in the responses. This is because the respondents are asked to select the best and worst (on a subjective scale) among a group of objects. The standard deviation of each respondent's unique best-worst score was computed to gauge the differences in the attribute's significance throughout the sample in order to better investigate data heterogeneity. The findings demonstrate that there is heterogeneity in the producers' responses to the most significant sources of risk to their farm business, since the standard deviation of all sixteen categories of risk (Column 7 of Table 4) is greater than one.

For each risk, the standard deviation to mean ratio was computed in order to assess the degree of response heterogeneity (Column 8 of Table 4). Ratios that are zero or almost zero imply absolute agreement or higher consistency in the degree to which a responder views a certain risk as important or not, whereas greater absolute ratios indicate greater variability in replies. The relative importance of the following hazards is more widely agreed upon: (1) price changes for products; (2) price changes for inputs; (3) leverage use; (4) rainfall variability; (5) technological developments; and (6) information security costs. However, the following factors exhibit more heterogeneity (as indicated by the standard deviation to mean ratio): (1) shifts in the global political or economic landscape; (2) natural disasters; (3) modifications to producer or governmental policies; (4) the level of debt to capital; (5) interest rate fluctuations; and (6) accidents and health/disability.

Latent class cluster analysis

To learn more about the type of heterogeneity in producers' responses to their perception of the most significant sources of risk, a latent class cluster analysis was calculated based on the observed heterogeneity in risk importance. According to Loose and Lockshin (2013), the latent class cluster approach makes the assumption that there are distinct data segments and that respondents have similar preferences within segments but differ across them. It identifies population segments and predicts each person's unique membership in a particular segment on a probability basis by using co-variation among individual observed preference scores (in this case, observed best-worst scores) as a measure of utility (Loose and Lockshin, 2013; Umberger et al., 2010). "The method assumes k latent groups or latent classes underlying the data set and that each case belongs to only one group and the number of classes and their sizes are not known a priori," state Ganesalingam et al. (2009: 2). Additionally, according to Coltman et al. (2011), the method enables the estimation of a maximum likelihood-based model that concurrently takes into account attribute similarities and differences. This study employed the latent class cluster approach to categorize producers according to their assessments of the relative importance of each source of risk to their farm operations and the ways in which the structural features of the farm and farmers affect these assessments.

Where y_i denotes an object's scores on a set of observed variables (in this case, the individual best worst scores for all the sources of risk and risk management strategies used as indicators or dependent variables in the cluster analysis), z_i represents object i's covariates, k is the number of clusters, $\Pi_{k \mid z_i}$ indicates the prior probability of belonging to latent class or cluster k given covariates z_i, J denotes the total number of indicators and θ is the model parameters.

In order to comprehend how respondents differ in their perceptions of the most important sources of risk, the dependent variable in the cluster analysis is the individual best-worst ratings for each of the sixteen sources of risk. In order to better anticipate each respondent's unique membership in the clusters that were discovered, farm and farmer characteristics were incorporated as explanatory variables that function as covariates in the cluster analysis. Off-farm income, farm size, household income, experience of the farmer, internal and external locus of control, risk attitude (assessed by means of a priori categorized questions in a Likert scale form), education, age, and gender are among the factors that are employed in the model.

In Latent Gold 5.1, we estimated a number of latent class models, and the model with the greatest fit was identified using the Akaike Information Criterion (AIC). The Akaike, Bayesian, and consistent Akaike information criteria, or AIC, BIC, and CAIC, are the most often used set of model selection procedures in latent class cluster analysis, according to Fraley and Raftery (1998). Because it considers parsimony by modifying the log likelihood goodness-of-fit values to account for the number of parameters in the model, the AIC was utilized as the criterion in the selection of the best model. This allowed it to address the issues of either under-fitting or over-fitting a model (Snipes and Taylor, 2014). The better the model fit, the lower the AIC value (Fabozzi et al., 2014). To make sure the model has a reasonable and relatively low ratio of classification error, other classification data, such as classification errors, were taken into consideration (Coltman et al., 2011). Since it had the lowest AIC value and the lowest ratio of classification mistakes, two separate classes were determined based on the information criterion and the classification errors.

The relative significance of the risk factors across segments is shown by the mean best-worst scores and latent class cluster features shown in Table 5. The cluster level conditional probabilities for each risk source are the basis for the mean best-worst scores, which show how important the risk is to producers.

The unique membership in a particular latent class was also found to be significantly predicted by a few factors, such as household income, age, external locus of control, debt-to-asset ratio, and off-farm income (Table 6).

With 64% of survey respondents in Cluster 1, it was the largest of the two clusters. We refer to producers in cluster 1 as "financial and business risk managers" because they view risk from financial, marketing, and production sources as crucial to their farm operation. The three biggest risks facing farmers in this cluster are variations in rainfall, input costs, and product pricing. For producers in the cluster, financial risks like interest rate fluctuations and the use of leverage (as indicated by debt-to-equity ratio) were also significant. Increased price volatility raises the cost of risk management (Tothova, 2011), and output fluctuations may result from rainfall unpredictability, endangering the stability of agricultural revenue. Given that these factors would impact their capacity to pay back loans when they become due, it may not be unexpected that farmers who are worried about leverage and interest rates view production risks as crucial to their operations.

Cluster 2 included the remaining 36% of responders. We refer to producers in cluster 2 as "production and marketing risk managers" because they place a greater emphasis on production and market risks as crucial to their farm business. Variability in rainfall, changes in product pricing, natural catastrophes, pests and illnesses, the capacity to satisfy quality standards, changes in input costs, accidents, and health and disability are significant hazards for these producers. Risks directly related to financial management are not included in cluster 2's top rankings. The fact that these farmers rely more on production contracts, which stipulate grade and protein qualities, may be the reason why failure to achieve quality criteria is ranked among the top dangers. For instance, the farm might be forced to fulfill the contract by buying the agreed-upon quantity of grain on the cash market if grain production falls short of the agreed-upon norm.One Compared to producers in the "Financial and business risk" cluster, those in the "Production and marketing risk management" cluster place a comparatively higher value on pests and diseases. Since pests and illnesses may have an impact on the grade achieved when production is delivered, these producers consequently also see the risk of achieving quality criteria as significant.

Lastly, producers who do not receive money from sources other than farming are 61% more likely to fall into the "Financial and business risk management" cluster, according to the results of the variables (Table 7). This might be a result of these producers' greater need to manage cash flow internally (in comparison to farms generating income from sources other than farming). On the other hand, people in the "Production and marketing risk management" cluster might be able to lessen the impact of decreased farm revenue or production by using their off-farm income. Since financial risk, as indicated by financial leverage, is not seen as a problem, producers with low debt-to-asset ratios are more inclined to focus on the sources of production risk, placing them in the "Production and marketing risk management" cluster. Farmers are more likely to fall into the "Financial and business risk management" grouping when debt levels rise. It's interesting to note that producers in the "Production and marketing risk management" cluster who did not think any of the financial risks were significant are more likely to have a debt to asset ratio of zero.

The findings also show that as farmers get older, their likelihood of falling into the "Financial and business risk management" cluster declines. This is in line with the usual trend of leverage use as the farm business develops. Additionally, people who think that external locus of control—the idea that risk in the farm is caused by forces outside of their control—are more likely to belong to the "Financial and business risk management" cluster. The majority of the hazards in the "Financial and business risk management" cluster are ones that farmers have less influence over, which may help to explain why a higher proportion of producers with external locus of control are located in this cluster. The "Financial and business risk management" cluster is more likely to include producers across all household income groups, but the likelihood declines with rising household income. The ability of farmers to fund their operations internally improves with rising household income, and these businesses may become less dependent on borrowing or other forms of outside funding. As a result, they might not see interest rate fluctuations and leverage as threats to their farming operation.

Conclusions

Like other business owners, farm managers have to recognize and control risk as part of their daily operations. Farmers are under pressure to find creative ways to preserve working capital and safeguard profits as the costs of machinery and other farm inputs continue to rise, increasing the money needed to remain in business. Furthermore, additional elements including erratic weather patterns, fluctuations in output costs, modifications to policies, and worldwide market patterns all add to the dangers that farmers must contend with. The ability to recognize these hazards and use the appropriate management techniques is a prerequisite for successful farm managers.

Despite the fact that every farm operator faces hazards, producers' perceptions of these risks vary. One of the earliest studies to demonstrate how various farms rank risk factors across a diverse sample of American farmers was that conducted by Thompson et al. (2019). We use a little more homogeneous sample set in our study to investigate a similar question. Using a count-based method, we discover that there is still a significant amount of variation in risk assessments even among a population of grain and oilseed farms in Saskatchewan, Canada. As a result, standardizing the risks that farmers encounter or assuming that each risk is equally significant to various farmer groups may result in unsuitable outcomes for management measures. According to other authors, a number of factors, such as farm type and location, as well as the risk management tools at hand, affect the sources of risk and how severe they are. Furthermore, a farmer's perception of a risk, farm and farmer characteristics, and the producers' perceived and real ability to handle these risks all influence how important a given risk is to them. This implies that farmers' perceptions of the kinds and levels of hazards they deem significant may differ depending on their location, making it necessary to comprehend these perspectives.

A sample of Saskatchewanian grain and oilseed farmers has been the subject of the analysis in this work. The methods used in this study and the Thompson et al.

(2019) study may be combined in future research. A producer sample with sector homogeneity but geographic heterogeneity may offer a rich environment for analyzing how location affects risks, as well as how manager variation impacts risks that could impact all producers equally (e.g., market access issues due to trade disputes). To help farmers lower output risks brought on by variations in precipitation during the growing season, the Alberta government, for instance, has implemented an agriculture drought and surplus moisture risk management plan.

Many producers might not have been reached by using online and internet-based surveys, particularly those who live in distant places where internet connectivity makes conducting online surveys difficult and time-consuming. However, based on the 2016 Census of Agriculture, which shows a notable gain in internet connectivity among Saskatchewan's agricultural population, we believe this worry is waning. According to Statistics Canada (2016), 51.2% of farms with internet connectivity have high-speed internet, out of around 61.3% that utilize it for farm operations. Although the literature on BWS suggests that sensory tiredness may become an issue, we made an effort to lessen this by limiting the number of tasks that needed to be completed.2.

According to our findings, Saskatchewan's grain and oilseed producers consider the following production and marketing risks to be significant to their farm business: (1) fluctuations in output prices; (2) fluctuations in rainfall; (3) fluctuations in input prices; (4) pests; and (5) illnesses. The findings on farmers' evaluation of their perceived sources of risk support the concern of farm managers for maintaining margins. According to our sample's respondents, risk variables that directly affect farm revenue are of more concern to them. Natural disasters, pests, diseases, and insufficient rainfall are a few examples of events that might lower output, which has an impact on the graded The BWS findings give government agencies and policymakers valuable information that should be used as a guide when creating new programs and raising awareness of existing ones created to control risk on farms. Governments should, for instance, keep looking at risk management instruments like AgriInsurance3 to make sure that coverage doesn't include typical risks that farmers can manage and instead concentrate on those that are beyond of their control. AgriInsurance's expanded coverage will help farmers manage risks by reducing the financial effect of production losses brought on by natural disasters. Furthermore, Canadian policymakers ought to put suitable plans into place to encourage a higher rate of AgriStability involvement.4. Increased involvement in margin protection programs will assist farmers in managing the risks associated with changes in input and output prices, which are significant risk factors for farmers in both clusters. According to the BWS data, all respondents agreed that "variation in output prices" is important for the agricultural industry. Producers also concur on the significance of hazards like "rainfall variability" and "variation in input prices." Respondents vary somewhat in how they evaluate the significance of the other dangers in addition to these three kinds of risk.

Both the cluster analysis and the BWS results show heterogeneity. It may not always be effective to promote a one-size-fits-all risk management technique due to the diversity of responses. For individual producers, a more focused strategy might offer better outcomes. For example, the aggregate sample assessed financial risks related to interest rates and debt-to-equity levels relatively low, while farmers in the "Financial and business risk management" cluster are highly vulnerable to these risks. Strategies that allow producers in this cluster to take advantage of discounts, like grouping purchases of seed and other farm inputs, may be beneficial. Additionally, respondents in the "Financial and business risk management" cluster are less likely to gain from off-farm income's ability to smooth income. This risk mitigation tool has been demonstrated to not only increase producers' ability to repay debt (Briggeman, 2011), but also to strengthen farm operators' ability to finance their operations internally and lower the percentage of farm revenue that is used for debt servicing, even though there may be a number of reasons why they do not earn off-farm income. Strategies that target all farmers can be advocated for other hazards that respondents in both clusters deem significant, such as: (1) fluctuation in output prices; (2) rainfall variability; (3) pests and illnesses; and (4) variations in input prices. However, it will also be required to implement initiatives that specifically target farmers in order to address the risks associated with production quality and finances.

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