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Managing Rail Logistics Risks Faced by Shippers: A Value-at-Risk Approach

In addition to the traditional market price risks, origin shippers of grains and oilseeds face risks related to the costs associated with the handling, storage, and transport of crops to their destination markets. To more closely examine the nature of these risks, a Monte Carlo optimization model was constructed using the Material Requirement Planning (MRP) methodology. The goal of the model was to minimize the mean and 5% value-at-risk (VaR) of the sum of these associated costs. The primary decision variable was the number of unit trains to purchase in the primary rail market. The model was also subjected to additional sensitivity and stress analysis to analyze the properties of the optimal results. A primary observation derived from this analysis is the importance of the primary and secondary railcar markets to the management of these risks, both from an informational and risk management perspective. Another key driver was the ability to manage the seasonality of farmer deliveries via forward contracting to capture returns to storage. Finally, another key contribution of this study is to demonstrate the utility of using subject matter expert (SME) time series modeling in Monte Carlo simulation.

Key Words: logistics, value-at-risk, material requirement planning, subject matter expert time series, primary and secondary railcar markets

Introduction

Railcar ordering strategies and freight costs have a substantial impact on risk and profits (or costs) for shippers. As a result, trading and risk management strategies related to car-ordering strategies have escalated in importance in recent years in part due to the emergence of the options now available to shippers. These mechanisms have resulted in alternatives available to shippers, each of which have varying risks related to both volatility in shipping costs and rail performance. Indeed, these mechanisms were subject to early legal proceedings (Interstate Commerce Commission 1992, United States Court of Appeals for the Eight Circuit 1993) and were subject to public scrutiny in 2013-14 (Kub 2015, Villegas 2016). In the end, the evolving instruments have continued to have prominent use in the grain trading industry, and similar mechanisms have been developed by each of the major railroads in the United States and Canada. These mechanisms pose challenges for trading firms and shippers, particularly with regards to risks related to shipping costs and rail performance in addition to the strategies employed by rival firms.

Grain shipping encompasses numerous risks which taken together can result in substantial gains or losses for shippers depending on strategies they adopt. Some of the important risks include the amount and timing of farmer deliveries, rail cost volatility in the secondary markets, rail performance (velocity) and railroad fuel cost surcharges (FSC). Sparger and Prater (2013) suggested that fuel surcharges are becoming a more important component of rail shipping costs with increases in the volatility of energy prices.

Current rail mechanisms require shippers to take positions for up to 12-36 months forward. However, a major source of risk is the amount and timing of farmer deliveries which is compounded by production risks, and growth in farmer owned storage. Earlier studies (MacDonald et al. 2004) indicated that the majority of grain deliveries (75% or more) are spot deliveries. Farmer deliveries are subject to substantial volatility and are highly seasonal which compounds shippers' primary rail market strategies — particularly those that have an option to contract for forward shipments up to 12 or more months forward. In particular, these forward rail ordering strategies are subject to the risk of rail car placements based upon the turnaround time (velocity) of trains, and are subject to cancellation penalties. As an alternative, rail shipments can be made under a secondary market instrument but, while these have more control over car placements, they are subject to higher and more volatile premiums which trade on a secondary market. Finally, since the early 2000's, railroads have frequently applied a 'fuel service charge' (FSC) which is an add-on cost that changes monthly based on changes in the reported price of on-highway diesel fuel by the US Department of Energy. All of these factors have complicated shipping and trading strategies for origin grain shippers relative to the regime of highly structured rates and pricing alternatives that existed prior to the 1990's.

Origin grain shippers (such as country elevators) are very adept at managing market risks related to grain pricing including the futures and basis components of the local cash price. Recently, more emphasis has been placed on utilizing advanced risk management tools such as value-at-risk (VaR) for the measurement and management of market price risks. These models have been adopted by larger grain (and energy) trading firms to measure and manage risks related to cash, futures, and option contracts. However, despite the current substantial risks in grain shipping, there have been few studies that have developed VaR models for the management of shipping and other related logistics costs, with the exception of applications to ocean freight risks (Alizadeh and Nomikos 2009).

The purpose of this paper is to develop a VaR model for measuring risks in grain shipping and logistics. We develop a Monte Carlo simulation model for a prototypical origin grain elevator shipping corn from North Dakota to the Pacific Northwest (PNW) export market. The model is based upon a Material Requirement Planning (MRP) specification (Ptak and Smith 2011) to estimate the logistics, handling, and storage costs associated with a predetermined primary shuttle train ordering plan for the upcoming marketing year. The primary VaR measurement metric of the model is the sum of all costs related to the storage, handling, and transportation of the corn from the elevator to the destination export market. A maintained assumption is that the shipper is completely hedged in terms of corn deliveries from local farmers and is obligated to purchase and handle all corn delivered either through forward contracts or spot deliveries from local farmers. Additionally, stochastic optimization was applied to the Monte Carlo MRP model to determine the optimal primary shuttle train ordering strategy under various assumed market conditions. This study is unique in that it applies the concept of subject matter expert (SME) time series models (Vose 2008) in simulating monthly projections for some of the relevant random variables.

This paper is organized as follows. In the next section, we provide background information and a review of the related studies and literature as it pertains to the evolution of rail transportation, rail mechanisms and pricing, basis and rail demand, and applications of VaR in shipping. This is followed by a section describes the structure and relevant calculations behind the Monte Carlo MRP model and the baseline assumptions. The baseline and optimized results are presented in the following section under various scenarios along with extensive sensitivity analysis to highlight and rank the key costs, risks and capacity variables that influence the VaR cost metric. This is followed by a section that draws out the key takeaways and conclusions from this particular case study model.

The topic addressed in this paper is important in several respects. First, grain origination firms are increasingly finding a need to develop and manage strategies to mitigate their exposure to risks in shipping. Second, there has been substantial heterogeneity in grain origination firms' profits in the past decade, depending in part on their use of these shipping instruments. Finally, though the focus of this study is on rail shipping strategies and risks, the problems addressed have similarities to both barge and ocean shipping.

Review of Relevant Studies

One of the features of the Staggers Rail Act (SRA) of 1980 was to allow for the use of contracts and varying forms of differentiation in rail pricing. Prior to the SRA, rail rates were primarily set by posted tariffs which limited the ability for carriers to revise rates, and railcars were allocated using varying forms of first-come-first-served mechanisms (Wilson and Dahl 2005). Without any cancellation penalties, many shippers placed "phantom orders" just in case they would need railcars in the future. Not surprisingly, these phantom orders led to an inefficient allocation of railcars.

In the immediate post-SRA period, confidential contracts were broadly adopted, but these eventually resulted in problems related to transparency and were biased in favor of larger shippers which affected competition in trading (Hanson et al. 1989, 1990). In response to these problems with the confidential contracts, railroads developed alternative market instruments which had several features including bilateral commitments for shipping costs and service for forward shipping periods of up to 12 to 36 months forward and were available to all shippers. Values for these instruments were determined by an auction mechanism, and the instruments were tradable. Initially, these were developed and adopted by the Burlington Northern Railroad and have since been widely adopted by most of the major Class I carriers in the United States and Canada.

These mechanisms resulted in what is commonly referred as primary and secondary market mechanisms[2]. The primary mechanism results in a certificate provided to the shipper when initially sold by the railroad in the auction. The primary market is the initial allocation of shuttles[3] in which shippers bid for rights to utilize a specified number of cars for a certain time period forward. The railroad offers shuttles for forward shipping periods, then the shippers bid, and the winners of each offering (the number of trains for each period) are allocated contracts for service. The contracts specify elements, such as the forward order period, rate level (tariff), and number of cars per month (Wilson and Dahl 2005).[4] An important feature of the primary market is transferability, which forms the foundation for the secondary market. This is important to shippers because there is substantial variability in shipping demand month-to-month due to intra-seasonal supply and demand levels (Wilson and Dahl 2005, 2011). The primary owner may

[2] Details of these vary by railroad, and through time, and are described in detail in Wilson et al. 2020.

[3] We use the term 'shuttles' to refer to the most common type of train used in grains and oilseeds. But, similar mechanisms exist and are used for alternative configurations of trains and cars.

[4] More formally, this takes the form of a k^{th}-priced sealed bid auction. Wilson and Dahl (2005) also developed a game theory bidding model of these mechanisms to evaluate critical factors impacting bid values.

choose to sell one or more trips to another shipper, while still retaining the rights to that train afterwards.

Another feature of the primary mechanism is that rail velocity (trips per month) determines the number of shuttles provided. Specifically, the shuttle owner receives a certain number of trips per month, which depends on velocity which is defined as trips per month. The actual shuttles received, referred as car supply, depends on the number of shuttles bought, velocity, and the number cars per shuttle, which is at the carrier's option (e.g., between 100 and 110 cars). The number of cars received (for a 110-car shuttle) is derived as:

$$C_a = V \cdot T_0 \cdot 110,$$

where C_a is the actual railcars received per month, V is the rail velocity (trains per month), T_0 is the number of shuttle trains purchased (ordered), and 110 is the number of railcars in each shuttle. This relationship is important in that velocity is random and results in a random number of shuttles provided by the carrier to the shipper. This essentially means that the shipper absorbs the quantity, or velocity risk, which compounds their shipping decisions and strategies.

The secondary market results from inter-firm transactions of certificates from the primary market. There are two main forms of inter-firm transactions that are commonly referred to as the secondary market. One is direct trading between shippers, and the other is an exchange between shippers through an intermediary third-party broker. These offers are published daily and come in a variety of formats. Typically, bids and offers (ask) are made for multiple periods forward. Important in the secondary market is there are inter-month differences in values (i.e., the 'carry') not dissimilar from the spreads in the futures and basis markets. There is very active trading of secondary instruments, separately for each railroad, and through multiple cash brokers, which are now subject to standardized trade rules (National Grain and Feed Association 2021).

The widespread existence of these mechanisms has resulted in a multitude of risks confronting shippers. These include farmer deliveries (total amount and seasonality), futures price and basis spreads that impact the return to storage, the secondary railcar market premiums or discounts (to tariff) which are referred as the daily car value (DCV), and the aforementioned railcar velocity. Shippers also confront risks related to oil prices through the fuel surcharge (FSC) which can be volatile in times of high energy prices. Finally, the distributions for these variables are important in modeling risks. Generally, these variables are risky, in several cases are highly skewed, and are correlated. For all these reasons, as illustrated in our model, it is important that trading firms integrate their marketing, storage, and shipping decisions.

While there is an extensive literature on risk management and basis modeling, there are only a few studies on the DCV. The evolution of the early rail car allocation mechanisms was described by Wilson and Dahl (2005). Previous studies on integrating shipping and trading decisions include Wilson, Priewe, and Dahl (1998), and Wilson, Carlson, and Dahl (2004). Early studies (Miljkovic 2001; Miljkovic et al. 2000) examined how rail and barge rates impacted grain shipping. Several recent studies analyzed the inter-relationships among the rail markets and basis values. Wilson and Dahl (2011) analyzed the relationship between interior basis values and the DCV. Bullock and Wilson (2020) analyzed the export basis for soybean and identified a large number of factors impacting this value, inclusive of the DCV. Wilson and Lakkakula (2021) analyzed the relationship between the export basis for soybean and DCV. Results indicated that the export basis and DCV were determined simultaneously, which has importance to trading strategies and risk. Finally, Lakkakula and Wilson (2021) analyzed the effects of shipping costs on the origin and export basis. Results indicated that the origin and export basis are determined simultaneously with each one affected by the dynamic variability of shipping costs.

Value-at-risk (VaR) is a single, summary statistical measure of possible financial losses that could occur at a small probabilistic frequency due to "normal" market movements (Linsmeier and Pearson 2000). The conceptual framework surrounding the VaR approach to risk measurement and management is not new — it has been around since the advent of probability theory and statistics as a formal science in the 1600's and 1700's (Bernstein 1998). The first modern application of VaR to business risk management dates back to the implementation of an informal capital test upon member firms of the New York Stock Exchange in 1922 (Holton 2003). VaR was further developed to provide a measure of risk for stock-held companies, and portfolios of stocks through the development of J.P. Morgan's RiskMetrics (J.P. Morgan / Reuters 1996) software in 1995. In the following years, RiskMetrics was widely applied in the financial and related industries (Jorion 2001).

The potential for applications of VaR in agriculture and commodity markets was laid out in a survey article by Manfredo and Leuthold (1999). They discussed and compared the three main methods of estimating VaR (i.e., parametric, historical simulation, Monte Carlo simulation) and how it would be well-suited for measuring and reporting risk in agriculture. In a later application paper, Manfredo and Leuthold (2001) demonstrated how VaR could be applied in measuring the risks related to cattle feeding margins. Wilson et al. (2007) demonstrated a case-study application of VaR to measuring and managing risk for a manufacturer of baked goods.

Gustafson (2004) reviewed the potential applications and limitations of VaR in agricultural budget analysis and lending applications. A particular limitation of VaR is the potential to yield biased estimates when loss functions are not normally distributed and in particular, exhibit fat tails (as is the case in many agricultural applications). One approach to this limitation is the application of extreme value theory (EVT) using the Generalized Extreme Value (GEV) distribution (Odening and Hinrichs 2001). Additionally, VaR violates the subadditivity criterion of a coherent risk measure (Artzner et al. 1999). This limitation can be effectively overcome through the use of tail loss estimates such as expected tail loss (Yamai and Yoshiba 2005) which is also often referred to as conditional value-at-risk (cVaR). Additionally, Daníelsson et al. (2013) pointed out that while VaR is not a globally coherent risk measure, it has remained a preeminent method of risk measurement that is preferred from an industry and regulatory perspective. They also showed that VaR meets the subadditivity criterion under a wide range of distributional assumptions with most violations occurring when coarse, empirical distributions (such as historical simulation) are used.

For commodity trading firms, risks related to shipping have become very important, as described above in the case of grains. Further, the fact that commodity firms have strategic alternatives for managing risks, the application of VaR for transportation and logistics risks seems fairly appealing. All the risks described above can be represented as distributions and used to develop a representative VaR model. However, most of the previous research related to VaR modeling of transportation and logistics risks has been in the area of ocean shipping. Angelidis and

Skiadopoulos (2008) evaluated ocean freight rates using VaR and found that the simplest non-parametric methods could be used to measure risk. Alizadeh and Nomikos (2009) suggested and illustrated VaR metrics related to ocean freight on bulk commodities. They indicated that performance testing of VaR models (such as back- and stress-testing) should be conducted due to some of the typical assumptions used in VaR modeling providing faulty risk mitigation indicators in some cases.

Chang et al. (2014) used VaR to measure long memory of dry bulk freight rates using the Generalized ARCH (GARCH) method of time series projection. Their study was one of the first to combine GARCH and VaR in shipping research. The empirical results suggested that precise VaR estimates may be acquired from long memory in volatility models. Alexandridis et al. (2018) used a portfolio approach to measure the profitability impact of significant volatility in dry bulk ocean freight rates. Furthermore, their study pioneered the portfolio approach to hedging dry bulk ocean freight. They found that implementing a portfolio hedging program could reduce total ocean freight cost fluctuations by up to 35 percent. Their study offered new insights into the effectiveness of using portfolio strategies, such as VaR, to hedge a ocean shipping position for grain.

Model and Assumptions

For this study, the base model assumed that the primary decision-maker is a large country elevator located in Jamestown, North Dakota that loads out and ships shuttle trains to the Pacific Northwest (PNW) export market. The elevator’s primary decision variable is the number of primary shuttle trains to purchase (same fixed amount per month) for the upcoming marketing year; however, many of the key variables in the model were not known with certainty and therefore, incorporated an element of risk. These were modeled using the Monte Carlo simulation features of the Palisade @Risk (Palisade Software 2021) software add-in to Microsoft Excel (Microsoft Corporation 2019). Table 1 contains the global parameter assumptions behind the base model.

Table 1. Global Parameter Values Used in Base Model

Global Parameter	Value	Source
Planning Date	8/31/2021	Case Study Setup
Location of Elevator Facility	Jamestown, ND	Case Study Setup
Crop to Be Marketed	Corn	Case Study Setup
Elevator Storage Capacity (mil bushels)	5.0	Case Study Setup
Shuttle Train Size (railcars)	110	BNSF Railroad
Capacity per Railcar (corn bushels)	3,700	BNSF Railroad
Rail Shipping Destination	PNW	Case Study Setup
Miles to Destination	1,407	Google Maps
Interest Rate on Storage (annual)	6.00%	Iowa State University, *Ag Decision Maker*
Other Variable Storage Costs (per bushel)	$ 0.04	Iowa State University, *Ag Decision Maker*
Forward Contract Percent	25%	MacDonald et al. 2004
Handling Cost (per bushel)	$0.30	Authors' Discussions with Industry Representatives
Railroad Tariff (per railcar)	$ 5,100	BNSF Railroad
Maximum Shuttles Loaded Per Month	6	Case Study Setup
Alternate Trucking Location[a]	Casselton, ND	Tharaldson Ethanol
Miles to Alternate Trucking Location	77	Google Maps
Trucking Cost (per bushel per mile)	$ 0.0040	E-mail from Industry Contact
Other Alt Destination Costs (per bushel)	$ 0.99	Author Calculations
Elevator Turnover Ratio (Modal Value)[b]	4.7	UGPTI, *Annual North Dakota Elevator Marketing Report, 2020-21*
Turnover Ratio Variation Percentage[b]	10%	Case Study Setup

[a]Only used for corn that cannot be shipped by rail or stored due to capacity constraints.

[b]Turnover ratio is multiplied by elevator storage capacity to determine annual farmer deliveries. Is modeled as a triangular distribution with minimum and maximum determined by the variation percentage applied to the model value.

The elevator has 5 million bushels of storage that is dedicated to corn which is located at multiple facilities. The planning date is set at the beginning of the 2021-22 marketing year. The elevator has the physical capability to load up to a maximum of six 110-car shuttle trains of corn per month. Each railcar can carry up to 3,700 bushels of corn; therefore, the elevator has the capability to load out on rail a maximum of approximately 2.44 million bushels per month (or approximately 50 percent of the total storage capacity for the facility).

The MRP Model Balance Table

The model assumes the elevator is required to handle (receive, store, and ship) any spot farmer deliveries as they occur. Total farmer deliveries during the 2021-22 marketing year are modeled as a multiple (turnover ratio) of the total storage capacity. Based on data from the Upper Great Plains Transportation Institute's (UGPTI) Annual North Dakota Elevator Marketing Report, 2020-21 (Vachal and Andersen 2021), the annual volume handle for elevators with unit train and/or 100-car rail loading capacity was 4.7 times the storage capacity for the 2020-21 marketing year (page 5). This implies a projected annual corn handle of 23.5 million bushels for the upcoming marketing year. To model uncertainty around total farmer deliveries, the annual turnover ratio is modeled as a triangular stochastic distribution with mode equal to 4.7 and the maximum / minimum values set at plus / minus 10 percent of the model value. This implies an annual corn handle that varies between 21.2 to 25.9 million bushels.

The Material Requirement Planning (MRP) specification is set up in Microsoft Excel in balance table format where the ending inventory for each month is equal to the following difference equation (all in million bushels):

$$I_t = I_{t-1} + K_t + D_t - S_t, \tag{1}$$

where I is the ending inventory, K is the farmer forward contract deliveries, D is the farmer spot deliveries, S is the total grain shipped, and $t = \{1, \ldots, 12\}$ is the month of the marketing year (September through August) for corn. For the initial month of the marketing year, it is assumed that the carryover inventory (I_{t-1}) is equal to zero bushels.

Monthly Farmer Deliveries

The base model assumes that farmer forward contract deliveries (K) represent a fixed percentage (25%) of the total modal deliveries (23.5 million bushels) that are spread evenly across all 12 months. In the base model, this would represent 490,000 bushels per month for a total of 5.88 million bushels across the marketing year. Note that this value is non-stochastic and is known with certainty for each month of the marketing year.

Since the MRP model only considers shipping, handling, and storage costs — the type of forward contract is irrelevant since the corn procurement cost from farmers is not included in the calculations. Therefore, all forward contracts can be treated the same in terms of grain volume. Also, the model assumes there is zero risk of performance on farmer forward contracts in terms of grain delivery.

The farmer spot deliveries (D) is treated as a random variable. First the total marketing year farmer deliveries is calculated as the randomly generated turnover ratio multiplied by the fixed elevator storage capacity. Then, the total marketing year spot farmer deliveries is calculated by subtracting the marketing year total forward contracted value from this randomly generated value. Then, the marketing year farmer deliveries are allocated across the 12 months of the marketing year by multiplying the marketing year total by a monthly percentage based upon historical North Dakota farmer deliveries based upon USDA-NASS data.[5]

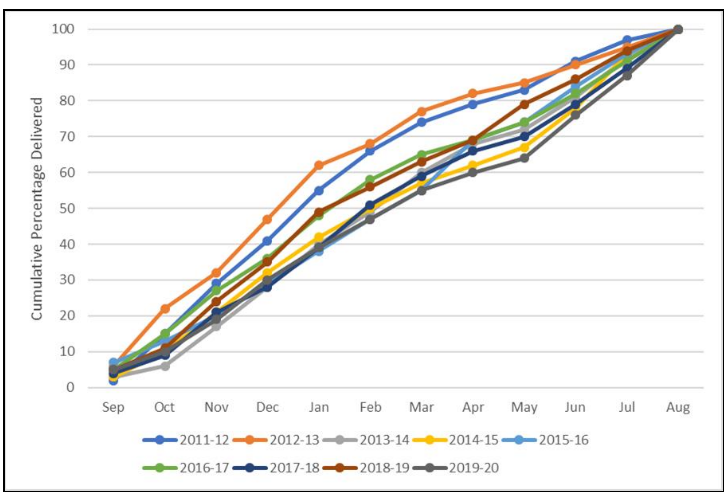

Figure 1. North Dakota cumulative farmer corn deliveries by month of marketing year (**source**: USDA-NASS, *Stats Online* database).

[5] Source is USDA-NASS *Stats Online* database located at https://quickstats.nass.usda.gov/.

Figure 1 plots the historical cumulative (%) farmer deliveries for North Dakota corn for the 2011/12 through 2019/20 marketing years. Each plot begins with the September percentage delivered and converges to 100% by the end of the marketing year. Note that the extreme drought year of 2012-13 stands out as extremely high harvest prices and a small crop resulted in a high percentage of early deliveries of farmer corn. Likewise, the strong production year of 2019-20 resulted in farmers holding off their deliveries until later in the marketing year. For the Monte Carlo simulation, one of the 9 marketing years illustrated was selected a random (with equal probability) and applied to the simulated total marketing year spot deliveries to derive the monthly farmer spot deliveries.

Monthly Grain Shipments

The total shipped (S) per month is calculated using a very simple and basic decision rule. First, it is assumed that the elevator has perfect foresight into the next month with regards to futures, basis, and secondary (DCV) railcar prices. With this information, the elevator is able to accurately project the DCV-adjusted net carry which is equal to (all prices in monthly average format):

$$AC_t = (F_{t+1} - F_t) + (B_{t+1} - B_t) - (i/12) \cdot (F_{t+1} + B_{t+1}) - VS_{t+1} - (DCV_{t+1} - DCV_t), \qquad (2)$$

where *AC* is the DCV-adjusted net carry for corn placed in storage in period *t*, *F* is the nearby CBOT corn futures price, *B* is the PNW basis, *i* is the annual interest rate on storage, *VS* is the other variable storage costs (besides interest), and *DCV* is the daily car value.

If AC_t is greater than zero for month *t*, then it is assumed that the elevator will store the entire available supply (equal to $I_{t-1} + K_t + D_t$) up to the maximum storage capacity. Any excess available supply will be shipped by rail (added to *S*) up to the maximum rail shipping capacity. If this limit is exceeded also, then any excess above this will be trucked to an ethanol plant in nearby Casselton, ND at the alternative destination cost (trucking cost plus price differential between PNW and Casselton).

If AC_t is less than or equal to zero for month *t*, then is it assumed that the elevator will attempt to ship the available supply up to the maximum shipping capacity. Any corn in excess of the excess shipping capacity will be placed in storage. If the remaining amount exceeds the available storage capacity, then the excess is shipped to the alternate market.

Also note that the alternate market is merely used as a vehicle for disposing of excess corn that cannot either be stored or shipped. This implies that the alternative shipping decision does not factor into the optimal decisions within the Monte Carlo MRP model. Rather, it is used as an accounting mechanism to account for the volume of corn that cannot be either stored or loaded out for rail conveyance.

Train Ordering Mechanics

The decision variable in the model is the number of primary shuttle trains ordered per month.

This decision is made on the decision date (August 31 2021) and cannot be changed once it is made. The same number of trains is ordered across all 12 months of the marketing year. The actual number of primary trains received is equal to the number of trains ordered multiplied by a monthly train velocity multiple that is random and varies by month. This amount is rounded to the nearest whole number to represent actual primary trains received during the month.

The base model requires that shuttle trains cannot be broken up and bought/sold as individual or subunits of railcars. This is a requirement of most railroad shuttle train programs including BNSF. Also, it is assumed that a train will not be partially loaded out — in other words, a shuttle will not be shipped with empty railcars. This imposes a high degree of lumpiness in the rail shipping units. If the model determines that the available supply of corn is to be shipped by rail, the total shipped amount is prorated across available trains until the remaining balance falls below the total amount for a shuttle train (approximately 407,000 bushels). This remaining balance is either put into storage (if enough is available) or it is shipped by truck to the alternate market.

The model allows the elevator to sell excess primary shuttle trains into the secondary market at a price equal to the rail tariff plus fuel surcharge plus daily car value (DCV) price multiplied by 110 railcars in the shuttle. Additionally, if the elevator has enough excess shipped corn after filling all of its primary ordered trains, it can acquire additional shuttle trains in the secondary market to ship the excess grain — provided that it is enough to completely fill the train with any excess going to storage or into the alternate market. The price paid for each ordered train is equal to tariff plus fuel surcharge plus DCV multiplied by the 110 railcars in the shuttle train.

The MRP Model Cost Metric

The primary measurement metric of the MRP model is the total net shipping, storage, and handling costs (in million \$) for the upcoming marketing year. This cost is calculated using the following formula (all in million \$):

$$TC = \sum_{t=1}^{12} \left(H_t + R_t^P + R_t^S + U_t - C_t \right), \tag{3}$$

where TC is the total net costs, H is the handling costs, R^P is the primary rail transportation costs, R^S is the secondary rail transportation costs, U is the alternate market costs, and C is the net carry over storage costs. The monthly total handling costs (H) is just equal to the fixed handling charge per bushel (\$0.30 from Table 1) multiplied by the total amount of corn shipped per month (S).

Rail Transportation Costs

The primary rail transportation cost (R^P) has three basic components. The first is the published rail tariff from Jamestown, ND to the PNW export market. This is a fixed \$5,100 per railcar and is the same across all 12 months in the model. The second component is the fuel surcharge which is calculated from a fixed pricing (per railcar per mile) schedule based upon incremental changes in the U.S. on-highway ultra-low sulfur diesel (ULSD) fuel price as published by the Energy Information Agency of the US Department of Energy. Table 2 shows an illustration of the fuel surcharge schedule used in the model. This surcharge is listed on a per railcar per mile traveled basis. This amount varies by month based upon a random time series forecast of the ULSD fuel price. The third component is the primary railcar market value which is fixed at $54.00 per railcar in the base scenario. As with the rail tariff, this value is the same across all 12 months in the model since, in practice, the shipper acquires the primary instrument for the entire 12-month period.

Table 2. BNSF Fuel Surcharge Schedule Used in Model

ULSD Price Between		Surcharge (per railcar per mile)[a]
Low	High	
$ -	$ 3.249	$ -
$ 3.250	$ 3.289	$ 0.01
$ 3.290	$ 3.329	$ 0.02
$ 3.330	$ 3.369	$ 0.03
$ 3.370	$ 3.409	$ 0.04
$ 3.410	$ 3.449	$ 0.05
$ 3.450	$ 3.489	$ 0.06
$ 3.490	$ 3.529	$ 0.07
⋮	⋮	⋮
$ 5.730	$ 5.769	$ 0.63
$ 5.770	$ 5.809	$ 0.64
$ 5.810	$ 5.849	$ 0.65
$ 5.850	$ 5.889	$ 0.66
$ 5.890	$ 5.929	$ 0.67
$ 5.930	$ 5.969	$ 0.68
$ 5.970	$ 6.009	$ 0.69
$ 6.010	$ 6.049	$ 0.70

Source: BNSF website, http://www.bnsf.com/ship-with-bnsf/pricing-and-tools/index.page (account required).

[a]For each $0.04 increase in ULSD price above $6.01, increase surcharge by $0.01 per mile.

The secondary rail transportation cost (R^S) also has three basic components. The first two (published tariff and fuel surcharge) are the same as for the primary market. The main difference is in the third value which is the secondary market daily car value (DCV) which varies by month based upon a random seasonal forecast model.

Alternate Destination Costs

The alternate market cost (U) is a fixed amount per bushel that is based upon two components. The first component is the truck shipping cost per bushel which is a fixed amount per bushel per mile ($0.004) multiplied the total highway miles between Jamestown and Casselton, North Dakota (77 miles). The second component represents the average basis differential between the PNW and Casselton markets over the previous marketing year (2020 / 21) which is an approximate discount of 99 cents per bushel. Combined, these represent a fixed cost of $1.298 per bushel for corn shipped to the alternate market and are representative of the prevailing costs during the base case period.

Net Carry Over Storage Costs

The net carry over storage costs (C) is equal to the following equation:

$$C_t = (F_t - F_{t-1}) + (B_t - B_{t-1}) - (i/12) \cdot (F_t + B_t) - VS_t, \tag{4}$$

where F is the nearby CBOT corn futures price, B is the PNW corn basis, i is the annual interest rate on storage, and VS is the other variable storage costs. This is essentially equation (2) with the *DCV* change removed since that cost is accounted in the secondary rail transportation cost component (R^S).

Stochastic Assumptions

Procedures for simulating the elevator turnover ratio and the monthly farmer spot deliveries were already discussed in earlier sections. For many of the key random variables in the Monte Carlo model, a technique known as *subject matter expert* (SME, Vose 2008) time series modeling was utilized to generate forecasts. The SME time series procedure simulates realizations of current and subsequent random values using autocorrelated random seed values. The initial seed value (ε_1) can either be randomly generated or set by the user. Each subsequent seed value is generated by the following difference equation:

$$\varepsilon_t = \rho \cdot \varepsilon_{t-1} + (1-\rho) \cdot \nu, \tag{5}$$

Where ε_t is the random seed for period t, ρ is the autocorrelation coefficient (between 0 and 1), and υ is a uniform random variable with a minimum of zero and maximum of one.

The logic behind the SME time series is that Monte Carlo time series paths for stationary distributions should exhibit a level of conditional statistical dependence between adjoining time periods. In other words, when an instance of a time series forecast generates an initial high percentile value of the forecast, then each subsequent forecasted value should also inherit a similar high percentile value with some ability for drift over time. The higher the value of ρ in equation (5), the less statistical variation between subsequent realizations of the forecast. This approach is extremely useful because it can be used to generate time series forecasts based upon essentially any univariate statistical distribution, including subjective distributions such as the triangular and PERT.

PNW Basis

Daily basis data (nearby futures) for PNW corn was obtained from Eikon (Refinitiv 2022) from January 2010 through August 2021. This data was converted into monthly averages. For simulating basis, a normal distribution was assumed to be the best fitting distribution. This is consistent with common practice since the limiting distribution of the difference of two lognormal price distributions is normal.

Table 3. Distributional Assumptions for PNW Basis
(Source: Refinitiv *Eikon*)

Month	Normal Distribution (cents/bu)[a]	
	Mean	St. Deviation
Sep	97.45	28.18
Oct	88.08	19.08
Nov	94.34	21.58
Dec	95.96	18.35
Jan	94.55	17.31
Feb	100.93	18.12
Mar	100.40	18.17
Apr	98.72	17.66
May	100.38	16.76
Jun	104.97	22.50
Jul	112.92	32.66
Aug	114.27	37.28

[a]Seed autocorrelation (SME time series) equals 83.1 percent.

Table 3 shows the historical means and standard deviations for the monthly PNW basis data. These values were incorporated into the @Risk normal distribution functions for simulation. The estimated one-lag autocorrelation (equal to 83.1 percent) for the historical monthly time series was used as the value for ρ to generate the autocorrelated seeds for the SME time series simulation of the forward basis values.

Futures Forward Curve

The CBOT corn futures forward curve was simulated using the assumptions from Black's (Black 1976) pricing model for options on futures. The Black76 model assumes the futures prices are distributed lognormal (normalized) with mean equal to the futures price and standard deviation equal to the value derived from the annualized option implied volatility.

Table 4. Futures Forward Curve Distributional Assumptions
(source: DTN *ProphetX* and CME Group Website)

Futures Month	LogNormal (Black76) Distribution Parameters[a]			
	Closing Price (cents/bu)	Implied Volatility (annual %)	Time to Futures Maturity (years)	Implied St. Deviation (cents/bu)
Sep-21	534.00	25.0%	0.038	26.15
Dec-21	534.25	30.0%	0.288	85.96
Mar-22	542.75	30.0%	0.534	119.01
May-22	547.75	30.0%	0.699	137.35
Jul-22	548.25	30.0%	0.868	153.28
Sep-22	517.25	30.0%	1.038	158.12

[a]Seed autocorrelation (SME time series) equals 90.0 percent.

Table 4 shows the values utilized in deriving the lognormal distributions for the futures forward curve on August 31 2021. Futures prices were from ProphetX (Data Transmission Network

2022) and the option implied volatilities were approximated by data on the Chicago Mercantile Exchange website (www.cmegroup.com). For months that lie between the listed futures months, linear interpolation was used to fill in the simulated prices. The SME seed autocorrelation was set subjectively at 90 percent to create a fairly tight simulated forward curve across the marketing year as is usually seen in practice.

Daily Car Values (DCV)

Historical weekly railroad secondary railcar market values (DCV) were obtained from TradeWest Brokerage's Daily Market Report for January 2010 through August 2021. This data was converted into monthly averages. A statistical distribution for each month of the marketing year was estimated on the historical data by using @Risk's *Batchfit* procedure using the Bayesian Information Criterion (BIC) to determine the best fitting statistical distribution.

Table 5. Bestfit Distributions for Daily (Secondary) Car Values (Source: Tradewest Brokerage, in $ per railcar)

Month	Distribution[a]	Shift Factor
Sep	Exponential (1056.90)	-339.83
Oct	Exponential (814.43)	-331.41
Nov	Exponential (327.05)	-367.23
Dec	Pearson5 (6.04, 6959.6)	-1156.30
Jan	Exponential (675.05)	-403.13
Feb	Exponential (886.15)	-289.47
Mar	InverseGauss (870.26, 303.45)	-285.84
Apr	Exponential (501.3)	-431.78
May	Exponential (361.99)	-347.67
Jun	Exponential (363.7)	-374.06
Jul	Loglogistic (-588.08, 568.79, 2.67)	#N/A
Aug	Exponential (675.36)	-512.53

[a]Seed autocorrelation (SME time series) equals 71.8 percent.

Table 5 shows the results of the Batchfit procedure. Note that DCV can be at either a positive or negative value historically; therefore, a shift parameter is incorporated to set a negative minimum value on the exponential, Pearson5, and inverse Gauss distributions. The historical monthly time series was used to estimate the SME autocorrelation (ρ) of 71.8 percent.

Railroad Velocity

Historical weekly railroad velocity values were also obtained from the TradeWest Brokerage Daily Market Report for the period between January 2010 and August 2021. This data was converted into monthly averages and the best fitting distributions were determined using the @Risk Batchfit procedure with the BIC used to determine the best fitting distribution.

Table 6. Bestfit Distributions for Rail Velocity
(Source: Tradewest Brokerage, in round turns per month)

Month	Distribution[a]
Sep	Triangular (2.43, 2.43, 3.10)
Oct	Triangular (2.06, 2.75, 2.75)
Nov	Triangular (1.95, 2.90, 2.90)
Dec	Triangular (1.77, 2.95, 2.95)
Jan	PERT (1.21, 2.78, 2.78)
Feb	Triangular (1.80, 3.00, 3.00)
Mar	Uniform (1.95, 3.24)
Apr	Uniform (2.06, 3.65)
May	Triangular (2.43, 2.43, 3.90)
Jun	Triangular (2.07, 3.04, 3.04)
Jul	Triangular (2.20, 2.20, 3.90)
Aug	PERT (2.54, 2.54, 4.27)

[a]Seed autocorrelation (SME time series) equals 73.4 percent.

Table 6 shows the best fitting distributions for each month of the marketing year. The historical monthly time series had a one-period autocorrelation of 73.4 percent which was used to set the autocorrelation factor in the SME time series simulations.

Railroad Fuel Surcharge

Weekly data from the website (https://www.eia.gov) of the Energy Information Agency (EIA) of the US Department of Energy was used to obtain the historical On-Highway ULSD fuel prices that are used to calculate the projected rail fuel surcharge. In this case, the @Risk time series fitting procedure was used to determine the best fitting time series model using the Bayesian Information Criterion (BIC) as the primary fit metric. Figure 2 shows the time series history along with the best fitting time series projection which was a differenced moving average process with lag 1 coefficient equal to 0.495 in value.

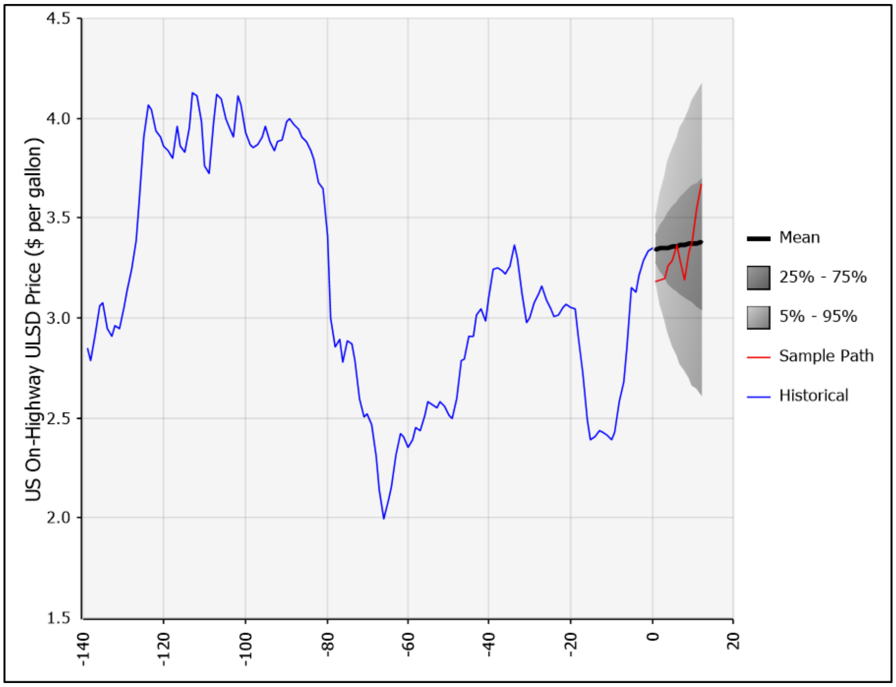

Figure 2. Plot of historical ULSD diesel fuel price with ARIMA (0,1,1) time series projection.

The simulated ULSD price forecast was incorporated into an Excel lookup table based on the BNSF fuel surcharge schedule (presented earlier in Table 2) to derive the appropriate fuel surcharge to use.

Correlations

Application of statistical tests indicated significant (p-value $\leq$ 0.10) Spearman rank-order correlations between PNW basis and DCV, and between DCV and rail velocity. Therefore, the generated uniform random variables in the SME seeds were correlated.

Table 7. Spearman Rank-Order Correlation Matrix Applied to Random Seeds

	PNW Basis	**Daily Car Values**	**Velocity**
PNW Basis	1.000		
Daily Car Values	0.249	1.000	
Velocity	(0.114)	(0.552)	1.000

Table 7 shows the Spearman rank-order correlation matrix used to generate the uniform random variables. As expected, the secondary railcar market values (DCV) are negatively correlated with rail velocity which is reflective of the supply of available railcars. Lower velocities would be indicative of a shortage which would lead to higher secondary market prices and vice versa. Likewise, the data indicates that the PNW basis is positively correlated with the DCV values which is consistent with the previous results from Bullock and Wilson (2020).

Model Simulation and Optimization

Convergence analysis of the mean and 95th percentile applied to the total cost metric indicated that both converged with a 1% tolerance level with 95% confidence at around 1,700 iterations. Therefore, the Monte Carlo model was set to run at 2,000 iterations for all simulations. To assure comparability and reproducibility of results across multiple simulations, the @Risk initial seed setting was fixed at '20220310' across all simulations.

To determine optimality in terms of primary trains ordered per month, an @Risk simulation table was set up to vary the number of primary trains ordered between 0 and 6 in decimal units for a total of seven simulation scenarios. The mean and 95th percentile of the total net shipping, storage, and handling cost metric were calculated for each of the seven scenarios and compared to determine optimality. Choosing the number of trains corresponding to the minimum mean cost would correspond to the optimal decision for a risk neutral decision maker. The 95th percentile is equivalent to the 5% value-at-risk (VaR) measure for a cost metric. Choosing the number of trains corresponding to the minimum VaR metric would represent a degree of risk aversion on the part of the decision maker.

Model Results

The Monte Carlo MRP base model was simulated to derive the optimal number of trains to buy from both minimum mean and minimum 5% VaR (95th percentile) of cost objectives. From the optimal VaR cost simulation, additional sensitivity analyses were performed to provide impact rankings for the key random input variables (farmer spot deliveries, futures and basis projections, daily car values, and fuel surcharge). For simplicity of presentation, these monthly random variables were aggregated into annual values using summation, averaging, and/or standard deviations where applicable and appropriate. These were derived using the standard @Risk sensitivity functions using the standardized regression coefficients as the ranking metric.

In addition to the base case scenario, additional sensitivities were conducted by either manually varying the global fixed parameters of the model, or by applying additional stochastic constraints on the random variables. For each sensitivity, the impact upon the optimal primary train ordering strategy from a minimum VaR perspective is analyzed along with summary statistics from the optimal case. These additional sensitivity scenarios included: **a)** examining the impact of using SME (autocorrelated seeds) versus not using SME (zero autocorrelation); **b)** varying the primary railcar price (base = $54 per railcar); **c)** examining situations where the daily car value (DCV) forward curve initial (September) value is constrained at a high (upper 25% of historical distribution) and low (lower 25% of historical distribution) value; **d)** varying the fixed forward contract percentage (base = 25% of modal farmer deliveries); **e)** examining the VaR minimizing optimal seasonal forward contracting strategy by allowing forward contracting to vary by month (base = flat even percentage across all 12 months); **f)** examining situations where the futures forward curve is in a strong inverse (minus two cents per month) and strong carry situations (plus three cents per month); **g)** constraining the initial (September) primary train velocity to a high (upper 25% of historical distribution) and low (lower 25% of historical distribution); and **h)** constraining all monthly primary train velocities to a shock low value of 1.5 trains per month.

Base Case

The Monte Carlo simulation results by number of purchased primary trains are shown in Table 8. For the risk neutral strategy of minimizing the mean total cost, the optimal strategy is to buy the maximum number of trains available. In fact, given the linear nature of the solution, the optimal strategy would be to always buy the maximum number of trains available. This is due to the difference in the mean daily (secondary) car value forward curve and the fixed primary railcar price of $54 per car which creates a strong incentive to speculatively buy as many trains as possible at the fixed price with the anticipation of being able to sell them later at a higher secondary (DCV) market value.

Table 8. Total Cost Monte Carlo Simulation Results by Monthly Trains Pre-Ordered (Base Case Scenario)

Monthly Trains Pre-Ordered[a]	Total Net Shipping, Storage, and Handling Costs (mil $)[c]		
	Mean	Standard Deviation	Value-at-Risk[b]
0	$ 37.71	$ 3.31	$ 42.83
1	$ 37.56	***$ 3.22***	$ 42.55
2	$ 37.40	$ 3.25	***$ 42.36***
3	$ 37.23	$ 3.41	$ 42.43
4	$ 37.07	$ 3.69	$ 42.66
5	$ 36.92	$ 4.05	$ 42.95
6	***$ 36.75***	$ 4.49	$ 43.34

[a]Number of trains per month ordered in primary rail market.

[b]Measured as 95th percentile of total cost distribution (i.e., 5% VaR).

[c]Optimal values highlighted in bold italics font.

For the extremely risk averse decision maker, the optimal strategy would be to minimize the standard deviation which would imply buying just one train per month. Given an average velocity of 2.5 to 3.0 trains per month, this would imply buying at around 50 percent of the maximum rail loading capacity (6 trains) of the elevator. For the moderately risk averse decision maker, minimizing the 5% VaR value would equate to buying two trains per month. At the previous mentioned average velocity, this would equate to approximately 80 to 100 percent of the monthly rail loading capacity.

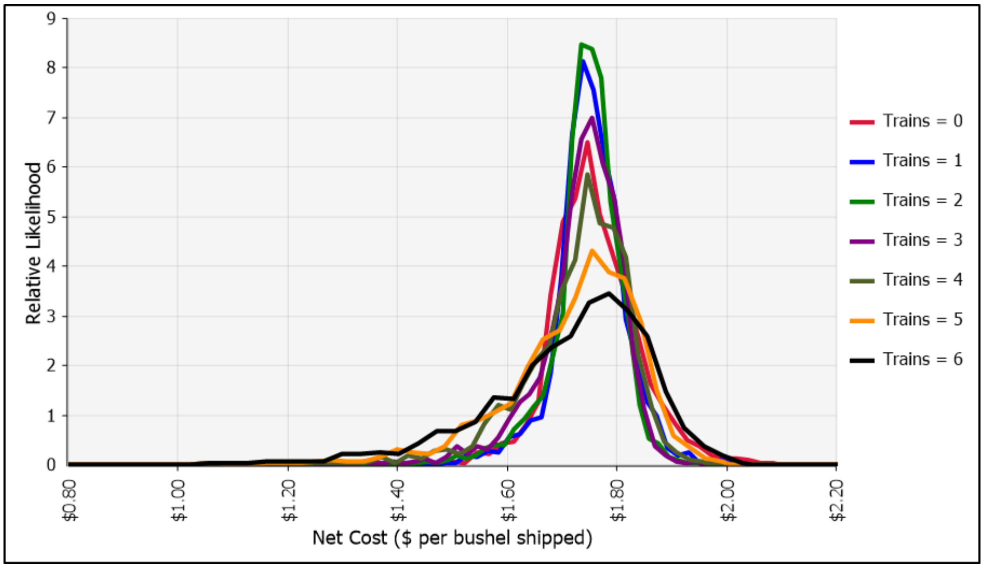

Figure 3. Base case simulated probability density functions for total cost by number of primary trains purchased per month.

Figure 3 illustrates the distributional impact of the primary train ordering strategies upon the net cost per bushel shipped. As the number of trains deviates from the risk optimal one or two trains per month, two impacts can be observed. First, the modal cost value increases when going down to zero or increasing above two primary trains per month. Second, the degrees of downside skewness (and volatility) increases when deviating from the risk optimal strategies. And third, the mean cost is pulled lower by the greater shift to the lower tails when compared to the increase in the upper tails of the distribution.

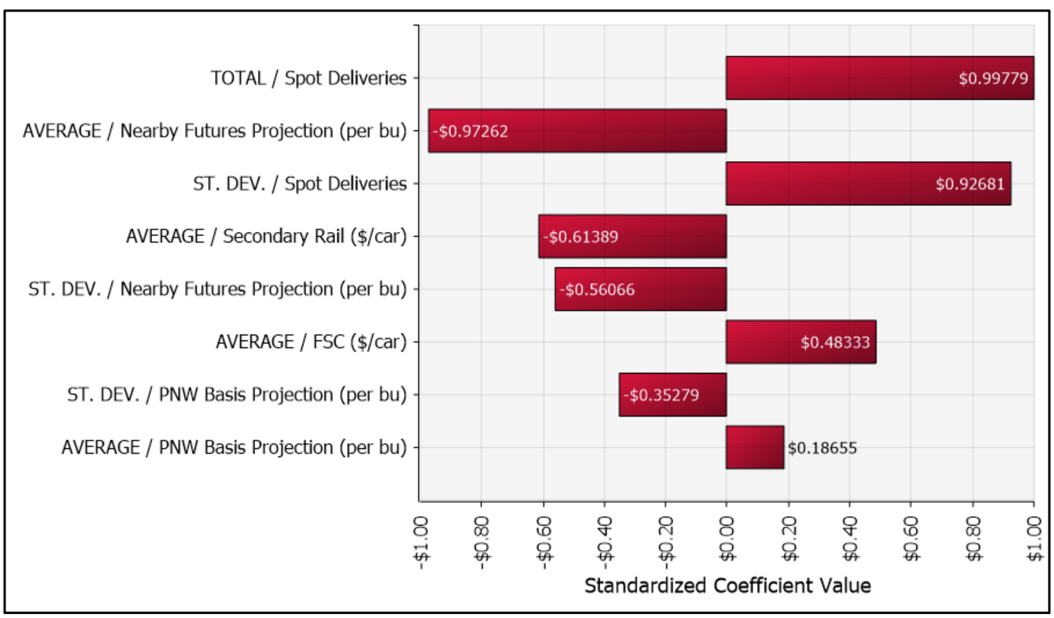

Figure 4. Base case sensitivity tornado for total costs (2 primary trains per month).

Figure 4 illustrates the @Risk sensitivity tornado for total costs (in million $) using the standardized regression coefficients for the ranking. The numerical values on each bar represent the average change in the total cost metric (in million $) given a one standard deviation increase in the input variable. The results show that the total cost is highly sensitive to changes in total farmer spot deliveries. This is indicative of the fact that as farmer deliveries increase, the amount of corn to be shipped increases which results in a higher total cost. Also, the seasonal volatility of farmer deliveries ranks third which provides added significance to the importance of the predicting and/or managing (via forward contracts) the farmer spot deliveries to manage total costs.

The second most important factor is the average 12-month projection of the futures forward curve. As the curve shifts to higher values, the potential for higher returns to carry increases, which results in the strong decline in total costs (due to offset versus storage costs). Combined with the significance of the futures volatility and basis average / volatility indicates that the net return to storage is an extremely important component in reducing total costs to the elevator.

The fourth most important factor is the monthly average of the secondary (DCV) railcar price which has a negative impact upon total costs. This follows from the fact that higher DCV results in higher profits from selling excess trains which were ordered at the fixed and lower primary railcar value.

Following DCV, the next most important input is the average fuel surcharge per railcar. As this is a cost add-on to both primary and secondary market-ordered railcars, it is not surprising that this has a positive relationship with the total cost metric.

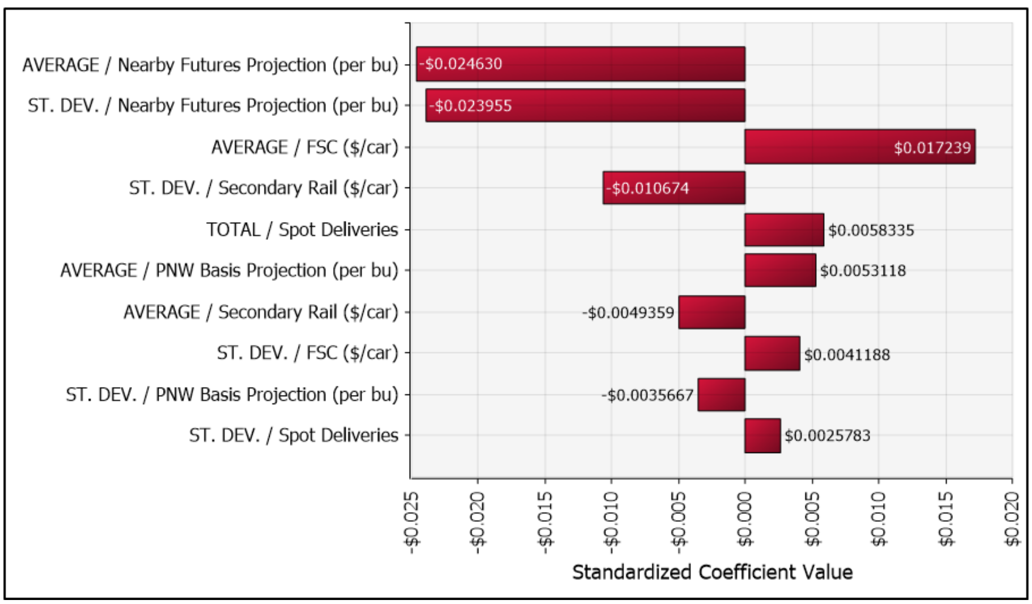

Figure 5. Base case sensitivity results for average cost per bushel (2 primary trains per month).

Figure 5 shows the base simulation sensitivity results using cost per bushel (instead of total cost) as the primary output metric. Total spot deliveries decline to fifth in ranking with the futures forward curve (MY average and standard deviation) elevated to the top two spots. The fuel surcharge moves above secondary rail (DCV) in ranking — primarily due to the fact that it is a cost component for both primary and secondary train shipments while DCV only impacts secondary trains. Also, the previously mentioned speculative role of DCV likely reduces its overall impact on cost per bushel.

Impact of Using SME Time Series

This study is novel in that it introduces the use of subject matter expert (SME) time series through the use of autocorrelated seed values. To illustrate the impact of using SME versus using independently simulated seasonal values, a sensitivity was conducted by setting the autocorrelation factors (i.e., ρ from equation 5) to zero.

Table 9. Total Cost Monte Carlo Simulation Results by Monthly Trains Pre-Ordered (Non-Autocorrelated Seeds)

Monthly Trains Pre-Ordered[a]	Total Net Shipping, Storage, and Handling Costs (mil $)[c] Mean	Standard Deviation	Value-at-Risk[b]
0	$ 32.67	$ 6.30	$ 42.23
1	$ 32.08	***$ 6.23***	$ 41.56
2	$ 31.45	$ 6.24	$ 40.72
3	$ 30.83	$ 6.34	$ 40.41
4	$ 30.22	$ 6.51	$ 40.19
5	$ 29.61	$ 6.76	$ 39.94
6	***$ 28.98***	$ 7.08	***$ 39.80***

[a]Number of trains per month ordered in primary rail market.

[b]Measured as 95th percentile of total cost distribution (i.e., 5% VaR).

[c]Optimal values highlighted in bold italics font.

Table 9 shows the optimization results when the autocorrelations are set to zero. The risk neutral (minimum mean) and extremely risk averse (minimum standard deviation) strategies remain unchanged from the base scenario. However, the minimum VaR strategy increases from 2 primary trains per month to the maximum of 6 trains per month.

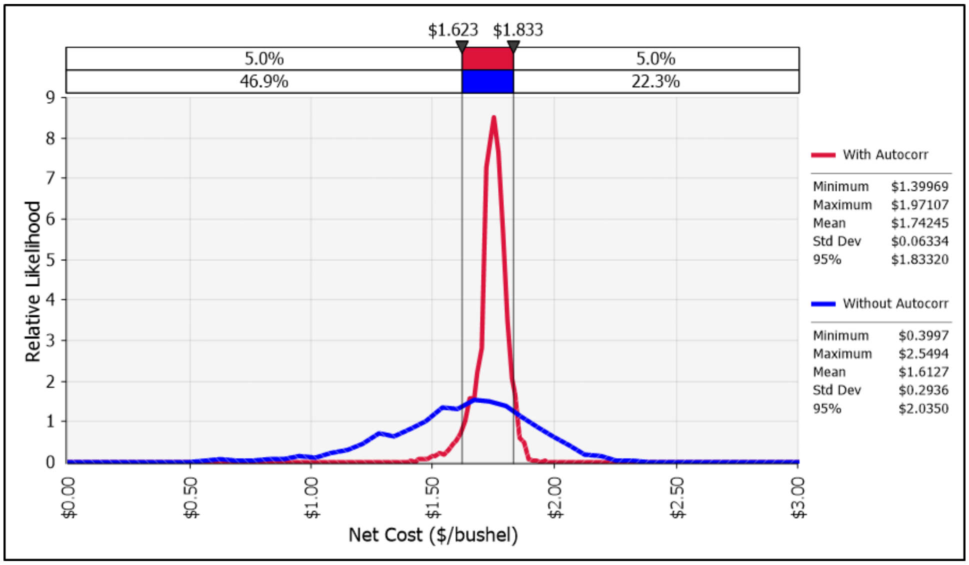

Figure 6. Impact of using SME autocorrelated seeds versus no autocorrelation.

The distributional effect on costs per bushel of using zero autocorrelated seeds is graphically illustrated in Figure 6. The primary impact is to drastically increase the standard deviation of cost. Given the negative skew of the cost distributions, this results in an even more pronounced decline in central moments (including mode) of the distribution. The negative central moment shift has a greater effect than the increase in variability which results in the VaR (95th percentile) declining more rapidly for the alternatives with lower mean costs.

Primary Railcar Market Values

The primary railcar market value is the price paid ($ per railcar) when buying (bidding on) primary trains. It is a fixed value across all months and in the base scenario, it is set at the long-term average value of around $54 per railcar. To examine the impact of this value upon the optimal primary ordering strategy and cost distribution properties, the MRP simulation model was evaluated at values ranging from $0 (the minimum value that can be offered) to $150 in $25 increments (with base $54 instead of $50).

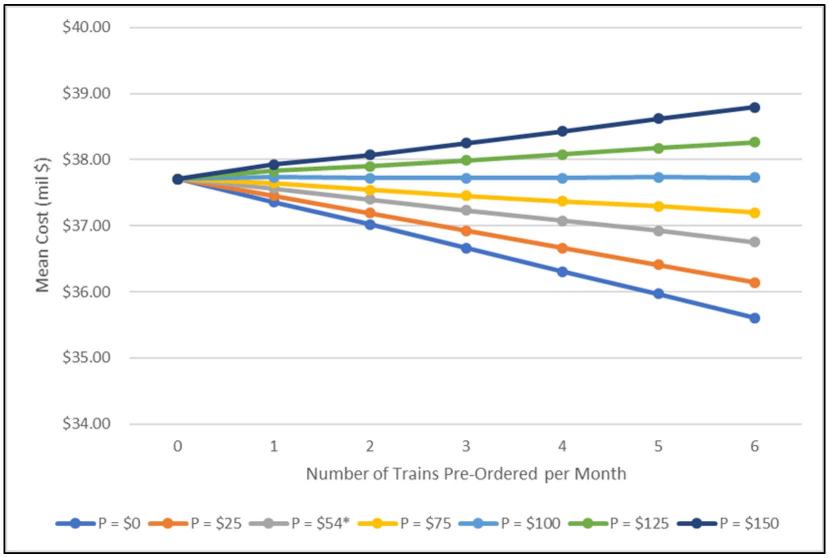

Figure 7. Sensitivity of mean total cost by primary railcar market price (*P*).

Figure 7 shows the sensitivity results for the mean total cost for the primary railcar values and number of trains bought. Note that as the primary railcar cost reaches $100 per railcar, the optimal result becomes almost indeterminate. For costs below $100, the optimal strategy is to buy the maximum number of trains available while for costs above $100 the optimal strategy shifts to buying no trains. The simulated DCV (based upon the fitted distributions for each month) results in an average cost (across the marketing year) of $109.56 per railcar. For primary railcar market values below this value, the risk neutral (minimum mean cost) rule would indicate buying the maximum number of trains and speculating on reselling excess trains at the higher secondary market value. For primary railcar values above the DCV average cost value, the risk neutral strategy would be to buy zero primary trains and buy needed secondary market trains at the lower average DCV value.

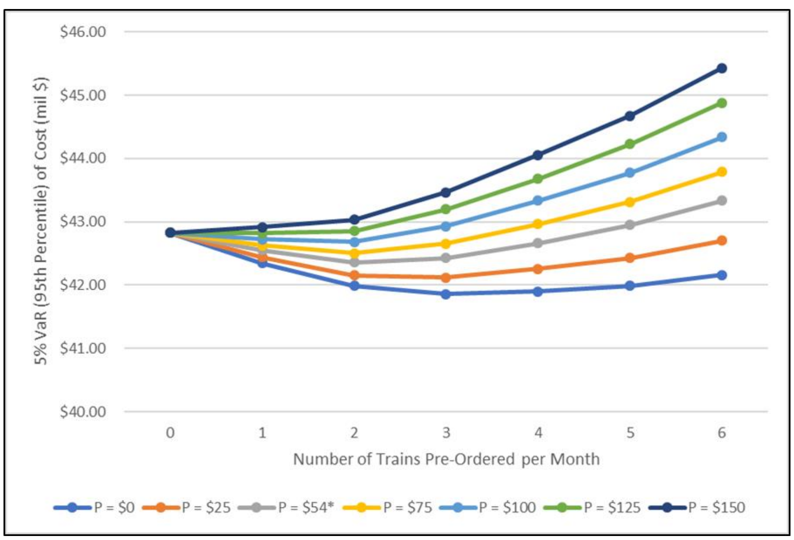

Figure 8. Sensitivity of total cost VaR by primary railcar price (*P*).

Figure 8 shows the VaR total cost sensitivity results by primary railcar value. For the two cost scenarios below the baseline, the optimal strategy shifts from buying two to three primary trains per month. For primary costs at $125, the optimal number of trains shifts down to one. For primary costs at $150, the optimal number of trains to buy shifts down to zero.

For the extremely risk averse decision maker (minimum standard deviation), the optimal result is unchanged at one train per month regardless of the primary railcar value. Examination of the cost distributions from the Monte Carlo simulation essentially shows the impact of changing the primary railcar value shifting the distributions from the left to right with the increase in primary railcar values. The standard deviations are mostly unchanged across the range of prices.

Secondary Railcar Market Values

The examine the effect of high and low secondary railcar market values (DCV), two constraints were applied to the base simulation model. Under the high DCV scenario, the initial seed (September) in the autocorrelated sequence was set to range uniformly between 0.75 and 1.00 which is the upper 25% of the fitted distribution. For the low DCV scenario, the initial seed was constrained to range uniformly between 0.00 and 0.25 which is the lower 25% of the fitted distribution.

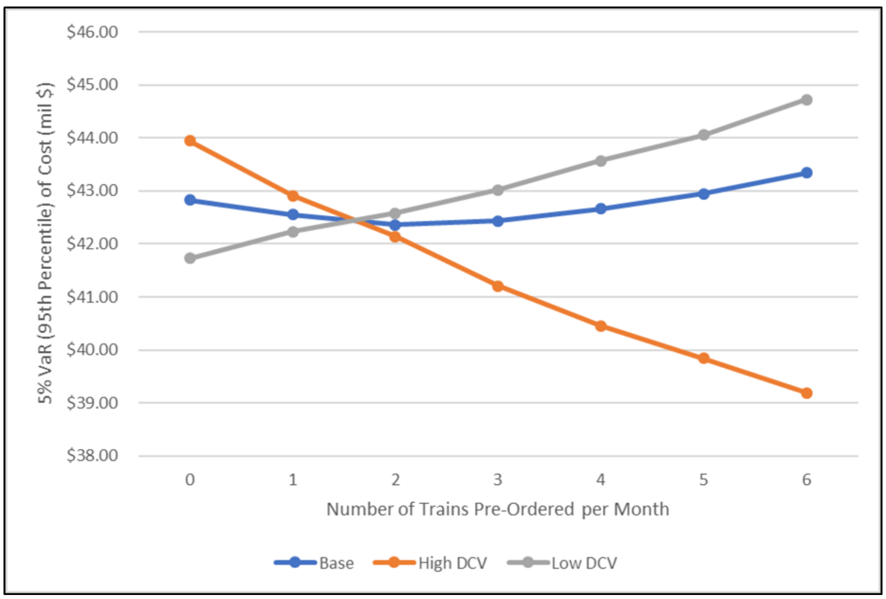

Figure 9. Sensitivity of total cost VaR to DCV scenarios.

Figure 9 shows the optimal total cost VaR results for the base and the two constrained DCV scenarios. The results indicate that for the low DCV scenario, the optimal strategy is to buy zero primary trains and ship all of the corn using lower cost secondary market trains. For the high DCV scenario, the optimal strategy is to buy the maximum number of available trains and speculate on selling off the excess trains into the high-priced DCV market. These results indicate that for the moderately risk averse (VaR minimizing) decision maker, having information even on the initial DCV prices could result in a more speculative approach to the buying of primary trains. Examination of the optimal results for each scenario indicates having information on the

DCV market posture ranges from $630,000 for the low DCV scenario to $3.17 million for the high DCV scenario.

Forward Contracting Percentage

In the base model, it was assumed that the forward contracting volume would be set at 25 percent of the modal value of the distribution for total farmer deliveries for the marketing year. This volume was assumed to be spread out evenly (equal percentage) across all 12 months of the marketing year. To evaluate the impact of forward contracting percentage upon the optimal primary rail strategy and cost distributions, this percentage was varied between 0 and 75 percent in increments of 25 percent.

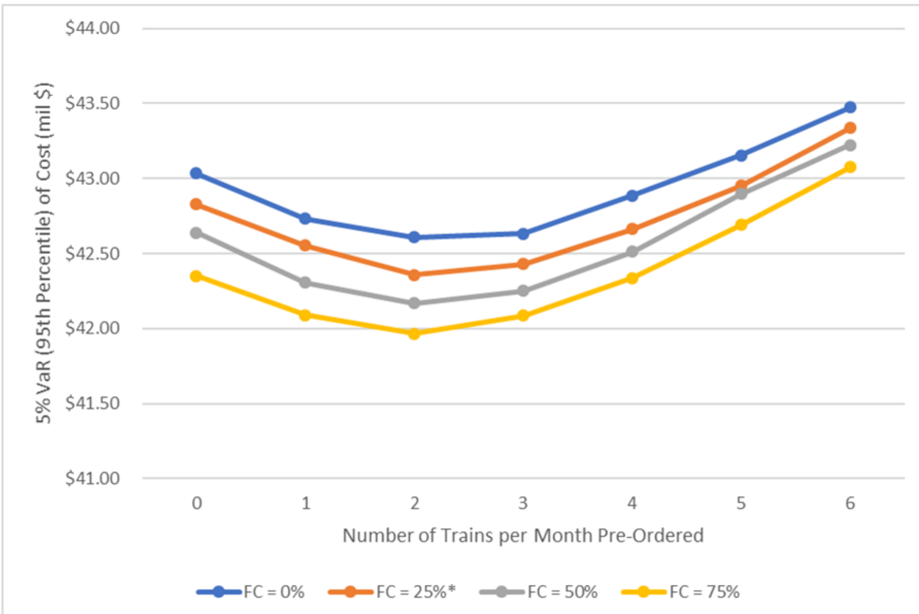

Figure 10. Sensitivity of total cost VaR to forward contracting percentage (*FC*).

Figure 10 shows the impact of total forward contracting percentage upon the optimal total cost VaR. The results show that the optimal number of purchased primary trains is unchanged at 2 trains across all of the forward contract scenarios. Reducing the forward contracting percentage to zero increased the VaR metric by a total of $250,000. Increasing the forward contracting percentage to 50% reduced total VaR by $190,000 while increasing to 75% reduced total VaR by $390,000 from the base scenario. For a given number of primary trains bought, the increase in forward contract percentage essentially reduced the standard deviation of the cost distribution with a smaller decline in the central moments of the distribution.

To examine the impact of a more seasonal forward contracting strategy, the monthly allocation of forward contracting volume was allowed to vary by applying stochastic optimization to the base model with the number of primary trains bought set at 2 trains and the total forward contracting volume set at 25% of the modal value (5.88 million bushels). To determine the optimal allocation, the *RiskOptimizer* stochastic optimization feature of @Risk was utilized. The optimization goal was to minimize the total cost VaR (95th percentile) by allowing the forward contract deliveries per month to vary from zero to 2 million bushels (40% of total storage capacity or 82% of total shipping capacity). The ‘budget’ optimization option was utilized to keep the sum of allocated volumes equal to the total forward contracting volume for the marketing year.

Table 10. VaR Minimizing Forward Contracting Strategy (Assuming 2 Primary Trains per Month)

	Forward Contracted[a]		
Month	Million Bushels	Percent of Total	Cumulative Percentage
Sep	0.00	0.0%	0.0%
Oct	0.00	0.0%	0.0%
Nov	0.00	0.0%	0.0%
Dec	0.00	0.0%	0.0%
Jan	0.00	0.0%	0.0%
Feb	0.00	0.0%	0.0%
Mar	0.00	0.0%	0.0%
Apr	0.00	0.0%	0.0%
May	0.00	0.0%	0.0%
Jun	2.00	34.0%	34.0%
Jul	1.88	31.9%	66.0%
Aug	2.00	34.0%	100.0%

[a]Total annual volume of 5.875 million bushels (25% of annual projected deliveries).

Table 10 shows the optimization results for forward contract volume. The optimal strategy is to allocate all of the volume into the final three months (June through August) of the marketing year. Seasonally, this the period with the strongest PNW basis and also higher futures prices (given the average 1.5 cent carry in the futures forward curve). This indicates a higher potential for earning returns to carry. This is also seasonally the period where DCV is lowest. The statistical impact of this optimal forward contracting strategy is quite large and significant. From the base case, the reallocation based upon optimization resulted in a $3.75 million reduction in the mean total cost and a $4.13 million decline in the total cost VaR. In addition, the standard deviation of total cost was reduced by $600,000 by employing the optimal contracting strategy.

Futures Carry

The base simulation uses the actual futures forward curve from August 31, 2021 for the mean of the simulated values. This curve had an average monthly carry of 1.5 cents per bushel for the months within the 2021-22 marketing year. For the alternate scenarios, the initial month (September 2021) futures price was left unchanged. For an inverse carry scenario, a 2 cent per bushel inverse was incorporated into the remaining futures prices through the marketing year. A stronger carry scenario was also implemented by using a 3 cent per bushel carry (double the base scenario). These alternatives were implemented evenly across the months.

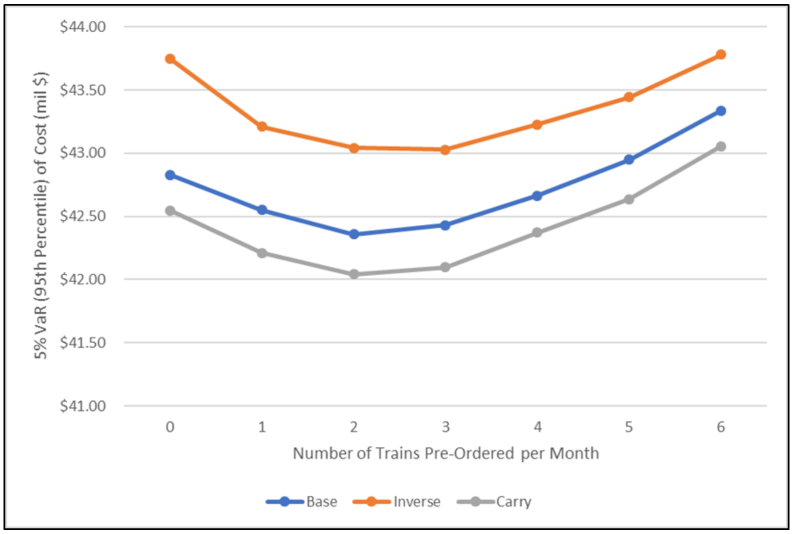

Figure 11. Sensitivity of total cost VaR to futures carry scenarios.

Figure 11 shows the total cost VaR results for the base and the two alternative scenarios. The optimal number of primary trains remained unchanged between the base and stronger carry scenarios at 2 primary trains. For the inverse carry scenario, the minimum VaR rule resulted in a one train increase to three; however, the change in VaR from two to three was minimal ($10,000 reduction).

In terms of the distributional impacts, the strong inverse scenario increased the mean total cost by $700,000 and the VaR by $560,000 with a $90,000 increase in the standard deviation. For the strong carry scenario, the mean cost declined by $610,000 and the VaR by $300,000 with a $30,000 increase in the standard deviation.

Rail Velocity

As with DCV, the high and low rail velocity scenarios were implemented by constraining the initial month seed to between 0.74 and 1.00 for the high scenario, and between 0.00 and 0.25 for the low scenario.

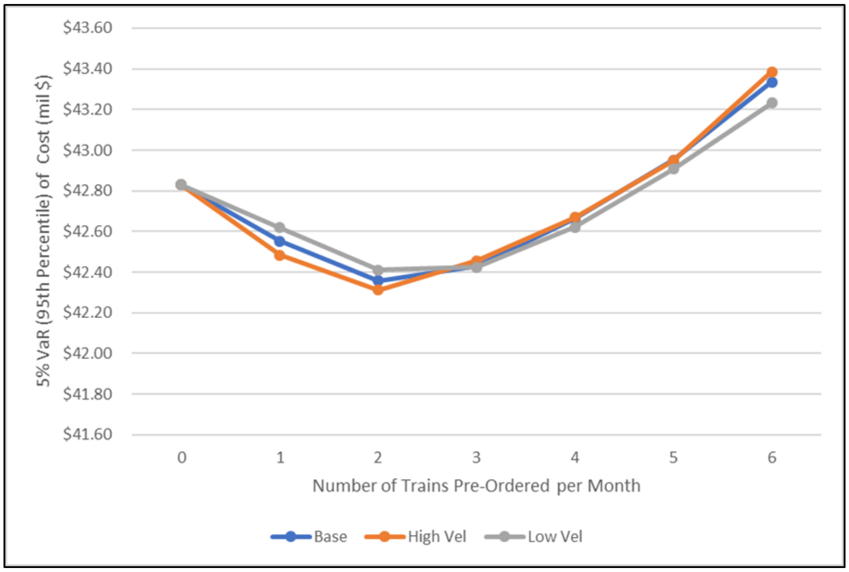

Figure 12. Sensitivity of total cost VaR to rail velocity scenarios.

Figure 12 shows the total cost VaR results for the base and two alternative velocity scenarios. The results for all three scenarios are unchanged at the base optimal strategy of buying two trains. However, for the low velocity scenario, the difference in VaR between 2 and 3 trains is quite small ($20,000).

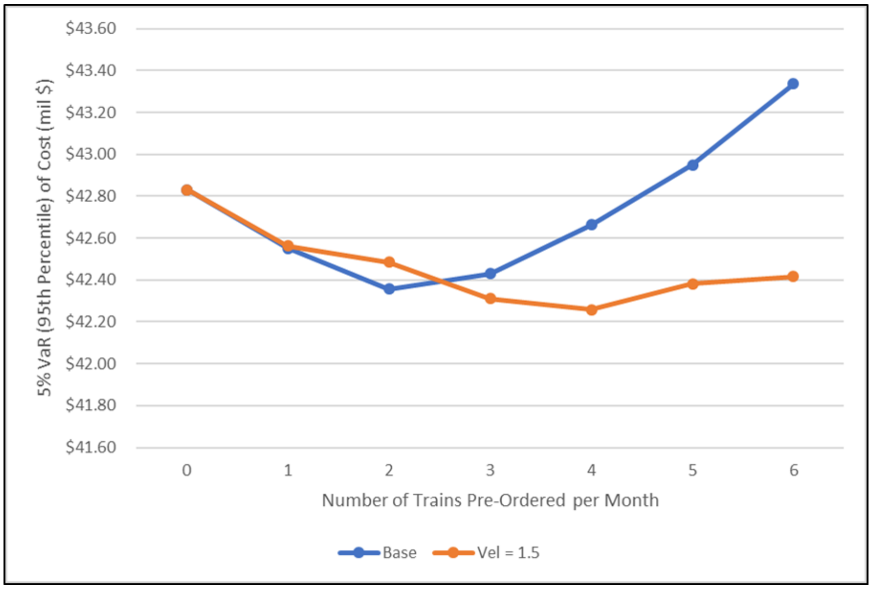

Figure 13. Sensitivity of total cost VaR to shock in rail velocity (fixed at 1.5 trains per month).

Statistically, there are minor differences in the cost distributions between the three scenarios. This is probably due to the small variation in the historical velocity distributions. Therefore, an additional scenario was examined where the velocity was fixed a very low value of 1.5 for each month. Figure 13 shows this shock scenario. In this case, the optimal number of trains to buy increases from two to four. With velocity fixed at 1.5, this implies a strategy of buying trains at

100% (4 x 1.5 = 6 trains per month) of the elevator's rail loading capacity. The distributional effect of the lower velocity (at 2 primary trains per month) is minimal with a $90,000 increase in mean cost and $110,000 increase in VaR. By increasing the primary trains from 2 to 4 reduces the VaR by $100,000 from the base scenario.

Summary and Conclusions

Commodity trading firms confront risks related to shipping which are seemingly escalating. These are apparent for ocean, barge and rail shipping, all of which have similar characteristics. These have become especially obvious given the current supply chain problems. The problems are important particularly in grain shipping by rail in North America in which shippers confront risks related to farmer deliveries of grain, the temporal structure of futures, basis and rail freight values, as well as rail car performance, fuel prices, etc. However, rail carriers have developed market mechanisms resulting in a "primary" contract market and a derivative "secondary" market (DCV), each of which have differing implications for managing risks. Ultimately, these mechanisms can be used to mitigate these risks, though not completely.

Because of the escalation of risks, commodity trading firms have become more focused on measuring and managing risks using the value-at-risk (VaR) methodology. Due to the escalating importance of risks related to logistics and shipping, there is an emerging interest among commodity trading firms in using VaR as a measure of risks related to these functions. In the case of shipping grain by rail using shuttle trains, there are many compounding factors impacting risk, as well as strategies that can be used to mitigate these risks.

The purpose of this paper is to develop a VaR model for measuring risks in grain shipping by rail. We develop a Monte Carlo simulation model for a prototypical North Dakota grain elevator. The model was based upon a Material Requirement Planning (MRP) specification to estimate the logistics, handling, and storage costs associated with a shuttle train purchasing strategy for an upcoming marketing year. The model was used to calculate the VaR related to these costs. The focus was only on the costs and risks associated with storing and shipping. Stochastic optimization was applied to determine the optimal shuttle train purchasing strategy under various market conditions and objectives. One objective was to simply minimize costs, and the other was to minimize VaR.

This study is unique in that it applies subject matter expert (SME) time series models (Vose 2008) in simulating monthly projections for some of the relevant random variables. The SME methodology allows for a more realistic simulation of time series connected to stationary statistical distributions using autocorrelated random seed values. The sensitivity conducted on the model with and without SME implemented indicated the difference in the results was drastic and consequential. In particular, without the SME methodology, the cost distribution increases substantially in variability and would likely overstate the true risk faced by the decision maker.

The results are insightful and illustrate the sources of risks and effects of risk mitigating strategies for the shipper. A primary result was if the objective is to minimize mean costs, the optimal decision was to buy the maximum number of trains (6 per month were allowed) which infers a speculative position on secondary market values. When risk aversion is introduced (via VaR minimization), the optimal number of primary trains falls to two per month which is closer to the maximum loadout capacity of the facility. This is a fundamental result and suggests that by ignoring risks, firms have an incentive to concentrate larger purchases in the primary market, given they have the option to sell surplus trains in the secondary market. This would be a less viable option for smaller firms.

Application of sensitivity analysis to the simulation results indicated that the volume and seasonality of farmer spot deliveries was the most important variable impacting the variability of total costs. Other important random variables include the futures forward curve which impacts storage returns, followed by the variability in the secondary rail market, and the fuel service charge. A key takeaway is the sensitivity results for the primary market railcar values. When values for the primary instrument exceeded $100 per railcar, the optimal strategy flips from 6 to zero primary trains per month for the mean cost objective function. This is reflective of the linear nature of the cost minimization solution. For the VaR strategy, the value drops from two to zero trains per month when the cost reaches $150 per railcar and increases from 2 to 3 trains per month as the primary railcar price falls to zero.

Another important result relates to the forward contracting strategy with growers. The minimization of the VaR of total costs resulted in the elevator spreading all of its forward contracting volume (25% of expected total farmer deliveries) across the final three months of the marketing year. This is the period corresponding with the strongest seasonal PNW basis illustrating the importance of returns to storage in the results. Compared to the base (even percentage across all 12 months), the optimized seasonal strategy significantly reduced both the mean and VaR of total costs.

Other results from the sensitivity / stress analyses are of interest. These are summarized using the VaR minimization specification. The optimal strategies under a higher DCV forward curve had an asymmetrically larger impact upon the reduction in mean and VaR of costs when compared to the optimal strategies under a low DCV curve scenario. The structure of the futures carry also had a significant impact upon the optimal and statistical results. Under a strong inverse carry (2 cents per bushel per month), the optimal number of primary trains increased from two to three per month for the minimum VaR optimization.

The results indicate that risks in the logistical functions are complicated, and the effects of risk mitigating strategies and measurement is compounded by these relationships. Hence, these results have implications for both shippers and carriers. As illustrated, VaR can be measured, and can be used as an alternative objective function. In addition, the VaR could also be used to set and monitor trading limits, etc. From a shipper's perspective, these results suggest that it is essential to integrate trading and shipping decisions. Treating these as separate functions would make risk management somewhat untenable. Second, optimal logistical decisions are impacted by numerous variables that include farmer deliveries which are highly random, followed by secondary market values for rail, railroad fuel service charges, and the distribution of futures and basis values. The results suggest that any way shippers could reduce the randomness in farmer spot deliveries would reduce the risks. Further, the structure of the forward curve (carry or inverse) impacts shipper risks and strategies.

It is important that rail carriers develop and provide these mechanisms for purposes of allocating rail cars, and to allow shippers alternatives to managing risks. Specification of primary contract terms has important impacts on shipper risk. As an example, over time, several carriers had developed mechanisms that disallowed transferability. Ultimately these failed due to the in ability of shippers to adapt to changing market conditions. It is important that further refinements take into consideration their impacts on shipper risks.

Finally, this paper has a number of contributions. First, it provides a detailed logistical model of a shipper that allows measuring risks using VaR. This extends previous studies in ocean shipping that propose methods to measure VaR in ocean freight. In rail, the risks are substantial and the mechanisms for managing these risks are more complicated. Second, the analysis identifies some of the critical areas of risks confronting rail grain shippers, and the effects of alternative strategies to mitigate these risks. Finally, the model uses SME time series which is a novel approach to specifying distributions, and as illustrated, has a substantial effect on the distribution of costs. To our understanding, this has not been used previously in logistics modeling.

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