Price Relationships and Feedstock Supply for a Second-Generation Ethanol Industry in Canada

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Agricultural and Resource Economics

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Abstract

There is potential for a second-generation ethanol industry that uses wheat straw as a feedstock to emerge in Western Canada. This thesis presents three analyses that investigate regional and international factors that influence the future success of this industry. The first two analyses investigate price relationships between markets related to the existing first-generation ethanol industry: Canadian wheat, and US corn, ethanol, and gasoline. The price of Canadian wheat is included to represent a market that may be closely linked to the supply of wheat straw, which could be a second-generation ethanol feedstock. The first analysis investigates time-varying relationships among these markets. Results suggest that the Canadian wheat market is positively correlated with the US corn and ethanol markets, which may be a significant source of the downside and upside risk to ethanol producers in the future. The second analysis investigates volatility transmissions among the same markets. Results indicate that Canadian wheat prices are not affected by price shocks or volatility in other markets. Still, volatility in the Canadian wheat market may influence volatility in the ethanol market. The first two analyses also find that there is a long run equilibrium price relationship between all markets, but that changes to this relationship only affect short term price movements in the wheat and ethanol markets. The results suggest that both the feedstock supply and the marginal revenue of second-generation producers could be susceptible to price changes in related markets. The relationship between agricultural prices and the supply of wheat straw is investigated in the third analysis. A dynamic programming model is used to analyze optimal crop and straw management decisions of a farmer under varying price processes and soil conditions. In general, results suggest that wheat straw supply is responsive to price but also depends on the amount of soil organic matter and whether there is a high risk of canola disease. Because these factors are spatially heterogeneous over the province, the availability of straw will also be heterogenous. Overall, the results of this thesis provide essential

information for the investment strategies of prospective ethanol producers and for policymakers who are interested in the emergence of renewable energy industries.

Table of Contents

Chapter 1: Introduction 1

Chapter 2: Prices for a Second-Generation Biofuel Industry in Canada: Market Linkages Between Canadian Wheat and US Energy and Agricultural Commodities 3

2.1 Introduction 3

2.2 Methods 5

2.2.1 Conditional Mean Specification 6

2.2.2 Volatility Model Specification 8

2.3 Data and Preliminary Tests 10

2.4 Results 15

2.5 Discussions and Conclusions 25

2.5.1 Results from VECM Analysis 25

2.5.2 Volatility Vulnerability and Persistency from DCC GARCH Results 27

2.5.3 Dynamic Market Interdependence from DCC GARCH Results 27

Chapter 3: Price Volatility Spillovers Between Canadian Wheat and US Energy and Agricultural Commodities 29

3.1 Introduction 29

3.2 Methods 31

3.2.1 Conditional Mean Specification 32

3.2.2 Volatility Model Specification 33

3.3 Data and Preliminary Tests 36

3.4 Structural Breaks and the BEKK-MGARCH Model 36

3.5 Model Results with Period Dummy Variables 39

3.5.1 Mean Equation Results 39

3.5.2 Variance Equation Results 40

3.6 Conclusions 44

3.6.1 Results from the VECM Analysis 44

3.6.2 Results from the BEKK-GARCH Analysis 45

Chapter 4: A Wheat Straw Feedstock Supply Response Model for Cellulosic Ethanol Production in Western Canada 47

4.1 Introduction 47

4.2 Methods 52

4.2.1 Dynamic Programming Overview ... 52
4.2.2 Surface Residue and SOM States ... 55
4.2.3 Expected Crop Yields ... 57
4.2.4 Expected Profits ... 59
4.2.5 The Dynamic Programming Model ... 60
4.2.5 Parameters and Constants ... 61
4.2.6 Agricultural Yields ... 63
4.2.7 Prices ... 67
4.2.8 Canola Disease ... 73
4.3 Results ... 75
4.3.1 Results within the context of Historical Straw Prices ... 75
4.3.1.1 The Value of Farmland ... 75
4.3.1.2 Crop Decisions ... 78
4.3.2 Structural Price Change: Ethanol Producers ... 89
4.3.2.1 The Value of Farmland ... 89
4.3.2.2 Crop Decisions ... 89
4.3.2.3 Decisions Regarding Sales of Wheat Straw ... 92
4.4 Conclusions ... 94
4.4.1 Farmer Decision Making ... 94
4.4.2 Implications for Ethanol Producers ... 95
Chapter 5: Conclusions ... 97
References ... 100
Appendix 1: Calculation of Dynamic Correlations ... 122
Appendix 2: Matrix Representation of the DCC-MGARCH Model ... 123
Appendix 3: Variance Equations of the BEKK Model ... 125
Appendix 4: Variance Equations of the BEKK Model with Dummies ... 126
Appendix 5: Natural Loss of SOM Calibration ... 127
Appendix 6: Solving the Bellman Equation ... 130

List of Tables

Table 2-1: Summary Statistics of Prices (n=513) 10
Table 2-2: Unit Root Test Statistics 13
Table 2-3: Summary Statistics of Price Changes, (n=513) 13
Table 2-4: Johansen Test for Cointegration 15
Table 2-5: VECM Results 17
Table 2-6: VECM results with DCC specification 20
Table 2-7: VECM-DCC Volatility Equation 21

Table 3-1: Nyblom Stability Test Results 37
Table 3-2: VECM with BEKK specification 39
Table 3-3: Nyblom Stability Test Results with Time Dummies 41
Table 3-4: Variance Equation Parameters of BEKK with Time Dummies 43

Table 4-1: Values of Model Parameters 62
Table 4-2: Summary Statistics of Yield Regression Variables 64
Table 4-3: Yield Regression Results 65
Table 4-4: Summary Statistics of Agricultural Prices 67
Table 4-5: ADF and KPSS Test Results 70
Table 4-6: AR (1) Model Estimation 71
Table 4-7: Prices Used in the Dynamic Programming Model 72
Table 4-8: Canola Disease State Transition Probabilities 73

List of Figures

Figure 2-1: Canadian Wheat and US Corn, Ethanol, and Gasoline Prices 12
Figure 2-2: Canadian Wheat and US Corn, Ethanol, and Gasoline Price Changes 14
Figure 2-3: Residuals from the VECM 19
Figure 2-4: Dynamic Correlation Coefficients 22
Figure 2-5: Average Dynamic Correlation Coefficients 24

Figure 4-1: Crop and Straw Management Decision Path 54
Figure 4-2: Scatter Plot of Wheat and Canola Yields vs SOM and the Yield Curves 66
Figure 4-3: Historical Straw Prices by AFSC Zone 68
Figure 4-4: Historical Wheat and Canola Prices, Northern Alberta PDQ Zone 69
Figure 4-5: Value of farmland for each canola disease state (CDS), SOM, and crop residue state combination. Wheat, canola, and straw prices are fixed at their means ($228.3, $479.4, and $51.7 per tonne, respectively). 77
Figure 4-6: Value of farmland under wheat and canola. Wheat, canola, and straw prices are fixed at their means ($228.3, $479.4, and $51.7 per tonne, respectively). Crop residues are fixed at the mean (8.1 t/ha). 80
Figure 4- 7: Value of farmland with varying wheat prices for Canola Disease State (CDS) 4. Panel (a) is the value of farmland under wheat and canola when wheat, canola, and straw prices are fixed at their means ($228.3, $479.4, and $51.7 per tonne, respectively). Panel (b) is the value of land under wheat and canola when the price of wheat is low ($214.4/t) or high ($242.1/t). VF is the value of farmland. 81
Figure 4-8: Value of farmland with varying canola prices for Canola Disease State (CDS) 4. The value of farmland under wheat and canola when wheat and straw prices are fixed at their means ($228.3 and $51.7 per tonne, respectively). The price of canola is low at point A ($448.2/t), average at point B ($479.4/t), and high at point C ($510.6/t). VF is the value of farmland. 83
Figure 4-9: Value of farmland with varying wheat straw prices. Change to the value of farmland when the price of wheat straw is high ($67/t). The price of canola and wheat are held fixed at their means ($228.3 and $479.4 per tonne, respectively). The crop residue state in panel (a) and (c) are held fixed at 8.1 t/ha. VF is the value of farmland. 84
Figure 4-10: The decision to harvest wheat straw. The price of wheat and canola are fixed at their means ($228.3 and $51.7 per tonne, respectively), and the price of straw is $63.5/t. 87
Figure 4-11: The decision to harvest wheat straw. The price of wheat and canola are fixed at their means ($228.3 and $51.7 per tonne, respectively), and the price of straw is $67.4/t. 88
Figure 4-12: When to Harvest Wheat Straw with a Structural Change in Wheat Straw Prices (prices are within the upper half of the new straw price distribution). 91
Figure 4-13: The minimum required straw price for each SOM level that is needed for a farmer to grow wheat and sell wheat straw. Wheat and canola prices are held fixed at their means, and the crop residue state is fixed at the mean. The blue points are linear extrapolations of the relationship between SOM and the price of wheat straw required for a farmer to sell wheat straw. 93

Chapter 1: Introduction

Not all biofuels are created equal. First-generation ethanol, which is ethanol commonly produced from sugar-containing materials like corn grain, wheat grain, and sugar cane, have been linked with social and environmental concerns surrounding intensive water use and pollution, higher and more volatile food prices, land-use change, and atmospheric pollution (Mohr and Raman 2013; Gasparatos et. al 2013). Second-generation ethanol is a potential solution to the environmental and social costs to first-generation ethanol because it can be produced from lignocellulosic biomass like agricultural residues (i.e. wheat straw, corn stover). Since 2010, nearly all the ethanol that has been produced in Canada has been made from first-generation feedstocks like corn and wheat grain (GAINS 2019). However, about 30 million tonnes of agricultural waste residues may be available every year for second-generation ethanol production in Canada (Littlejohns et al. 2018). Despite an abundance of potential feedstocks, second-generation ethanol production is not commercially established in Canada.

Economic barriers have limited the commercial production of second-generation ethanol. The amount of capital that is required to build and operate second-generation ethanol facilities is significantly greater than first-generation biofuel facilities (Bitnere and Searle 2017). For investors and creditors to provide the necessary capital, they need to ensure that second-generation ethanol operations are financially viable over time. Several key factors can affect the financial success of second-generation ethanol producers over time, namely feedstock cost and feedstock cost variability, feedstock supply variability, renewable fuels policies, and energy price volatility (Alfano et al. 2016; Bitnere and Searle 2017; Padella, O'Connell and Prussi 2019; Chen and Smith 2017). Therefore, it is vital for current research to investigate these issues if a second-generation ethanol industry is to emerge in Canada.

The purpose of this thesis is to investigate commodity price relationships and the supply of second-generation ethanol feedstock, which are two key elements that affect profitability, to inform investment strategies of prospective producers. Three studies are conducted as part of this investigation. The first two studies are macro-level investigations that explore the relationships among markets related to the first-generation ethanol industry: Canadian wheat and US corn, ethanol, and gasoline. The price of Canadian wheat is included in these studies to represent a market that may be closely linked to wheat straw, which may be used as a second-generation feedstock. Using time series econometrics, the first study investigates the dynamic interdependencies between markets. The second study analyzes price volatility and volatility spillovers among the four markets. The relationships among these markets, and the implied price dynamics, could inform risk management strategies of prospective second-generation ethanol producers. The third study is a micro-level investigation into the management decisions of farmers in Alberta, Canada. The objective of this study is to understand how the supply of wheat straw could change spatially and temporally, given that farmers have options to (1) grow wheat and retain wheat straw, (2) grow canola, and (3) grow wheat and sell wheat straw. Information regarding the supply decisions of farmers in Alberta could be used by ethanol producers and policy makers to understand how responsive the supply of wheat straw is to agricultural prices and farm productivity.

Chapter 2: Prices for a Second-Generation Biofuel Industry in Canada: Market Linkages Between Canadian Wheat and US Energy and Agricultural Commodities

2.1 Introduction

Federal and provincial governments in Canada require renewable fuels like ethanol to be blended with gasoline to reduce greenhouse gas emissions (Government of Canada 2017). First-generation ethanol that uses crop grains like corn as a feedstock has been linked with higher crop and food prices (Zhang et al. 2013). Second-generation (i.e. cellulosic) ethanol that uses crop residue waste as a feedstock may alleviate this concern, because the supply and price of crop residues may not affect crop prices. Although a market for second generation ethanol made from agricultural residues does not currently exist in Canada, residues from wheat represent a potential feedstock. The Western Canadian provinces (i.e. Alberta, Saskatchewan, and Manitoba) produced twenty-eight million tonnes of wheat in 2016, which was approximately 87% of all wheat produced in Canada (The Government of Alberta 2018). Because wheat straw is a by-product of wheat grain production, factors that affect Canadian wheat grain prices may affect the price and availability of wheat straw as a feedstock for second-generation ethanol. Therefore, prospects for a second-generation biofuel industry using wheat straw depend on future patterns of Canadian wheat prices and related markets, which could be influenced by interdependences among these markets. In this study, we investigate markets for corn, wheat, gasoline, and ethanol. Ethanol is related to these other markets in several ways. First-generation ethanol currently uses corn and wheat grain as inputs, which may, in turn, be related to agricultural commodities. Ethanol and gasoline markets are also potentially related, as ethanol is an input for gasoline due to renewable fuel standards.

The extent to which these markets have become and could become integrated is important for potential investors. Ethanol producers looking to invest in Canada want to understand if there is a significant relationship between input and output prices, and how the wheat and related market prices may be affected by general economic conditions. There may be a substantial degree of downside and upside risk to ethanol producers in situations where prices between these markets are interdependent. Therefore, understanding price relationships provides useful information for investment decision making. The purpose of this paper is to analyze whether and to what extent Canadian wheat and US ethanol, corn, and gasoline markets are interdependent.[1]

Previous literature that looks at interdependences between energy and agriculture commodities primarily focuses on large ethanol markets such as the US, Europe, and Brazil. This literature makes contributions to the "food versus fuel" debate by analysing market interrelationships in the context of how gasoline, oil, and first-generation ethanol (e.g. ethanol made from corn and sugarcane) affect global food prices (Chen et. al. 2010; Creti et. al. 2013; Du et. al. 2011; Nazlioglu 2011; Allen et al. 2018; Hameed and Arshad 2009; Chakravorty et. al. 2017; Saghaian 2010; Hao et. al. 2013; Serra 2011). In general, the authors find that ethanol markets are integrated with agricultural markets, but the direction and magnitude of relationships vary. For example, large markets like crude oil, corn, and sugar, tend to lead smaller markets like ethanol. Serra (2011) observes that Brazilian sugar prices affect Brazilian ethanol prices in the long run, and that ethanol prices affect neither sugar nor oil prices. Instead, Brazilian sugar prices are mostly dependent on local Brazilian sugar yields. Allen et. al. (2018) find that the direction and magnitude of causal relationships between sugar and ethanol prices change depending on whether the prices

[1] It is assumed that Canadians are price takers with respect to international ethanol, corn, and gasoline markets, which are reflected by US prices.

are in a high or low volatility environment, and that corn and ethanol prices have a significant long run relationship. The existing literature has produced evidence that international agricultural and energy market relationships tend to be dynamic and not static across time.

A Vector Error Correction Model (VECM) with a Dynamic Correlation Coefficient-Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) specification is used to quantify pairwise relationships between price changes among markets. Weekly data from June 2008 to July 2018 is used. This research helps to better understand interdependencies among current markets, and contributes to benchmark information, to inform alternative future price scenarios. Such information can help to further develop relevant policies and strategies that may be employed to promote a second-generation ethanol industry in Western Canada based on wheat residues.

In the next section, the econometric approaches are presented. Section 2.3 discusses the data used, while Section 2.4 presents the results. Section 2.5 summarizes the conclusions of this analysis and discusses the implication of the results for an emerging second-generation ethanol industry.

2.2 Methods

The time-series analysis consists of estimating mean and volatility equations together as a system using the maximum likelihood method.[2] The mean equation is a VECM and the volatility equation is a MGARCH model with a DCC specification. Engle-Granger (Engle and Granger 1987) and Johansen cointegration tests (Johansen 1991) are used to identify long-run relationships between each of the price series. Once the cointegrating equations have been identified, a VECM

[2] The Berndt-Hall-Hall-Hausman (BHHH) algorithm is used to estimate the DCC-MGARCH system.

is employed to model the short and long-run relationships between each of the price series. The DCC-MGARCH specification is used because the purpose of this paper is to identify the extent to which Canadian wheat has become integrated with US corn, ethanol, and gasoline markets. Specifically, the DCC-MGARCH model is used to generate time-variant conditional correlations and volatility, measured as standard deviations, between markets (Engle 2002).

2.2.1 Conditional Mean Specification

An introduction to the concept of cointegration can be gained from Murray's (1994) anecdote about an inebriated man and his dog. If we were to track the path of the inebriated man and his dog from one side of a park to another, it would not be inherently clear that there is a relationship between the two. The inebriated man stumbles along from one side of the park to another, while the dog runs around distracted by other dogs, people, birds, etc. However, the inebriated man and the dog enter and exit the park together because there exists a long-run relationship between the two. An Engle-Granger cointegration test can identify if this kind of relationship exists in time series data. The Engle-Granger cointegration test is a two-stage process that begins by regressing a dependent variable, in this case wheat prices, on the independent variables, in this case prices of corn, ethanol, and gasoline. Then, the first differenced residuals are regressed on the lagged level of the residuals. The null hypothesis is that the residuals are not stationary, which implies that the price series are not cointegrated and follow unit root processes (i.e. the estimated coefficients on the lagged residuals are equal to one). The alternative hypothesis is that the residuals are stationary, and therefore the price series are cointegrated. If the price series are found to be cointegrated, they can be modelled with a VECM.[3] The general VECM specification is:

$$\triangle p_t = \alpha + \sum_{i=1}^{j} \Gamma_i \triangle p_{t-i} + \Pi p_{t-1} + \varepsilon_t \tag{2.1}$$

$$\text{where} \quad \Pi p_{t-1} = \theta(\mu' p_{t-1})$$

The dependent variable, $\triangle p_t$ is a $K \times 1$ vector of price changes (i.e. percent change in price) in period, t, where K is the number of markets under consideration in this analysis. The α is a $K \times 1$ vector of constants and ε_t is a $K \times 1$ vector of residuals. The VECM considers the short-run and long-run relationships between each market. The short-run effects are captured by, Γ_i, which is a $K \times K$ matrix of estimated parameters on the $K \times 1$ vector of lagged price changes, Δp_{t-i}. The long-run effects are captured by the error-correction process, Πp_{t-1}. The $K \times K$ coefficient matrix, Π, is a function of a $K \times r$ matrix[4] of error-correction parameters, θ, and the transpose of a $K \times r$ cointegrating equation matrix, μ. The matrix operation $\mu' p_{t-1}$, where p_{t-1} is a $r \times K$ matrix of lagged prices, will yield a $r \times 1$ vector of cointegrating equations. Each element of the estimated $K \times r$ vector of parameters on the error-correction process, θ, can be interpreted as the speed at which the respective dependent variable adjusts to a deviation in the long run equilibrium relationship.

[3] Before the VECM model is estimated, an Engle Granger test and a Johansen cointegration test are performed in Section 4 to specify the mean equation.
[4] The *r* dimension represents the number of cointegrating vectors.

2.2.2 Volatility Model Specification

The DCC-MGARCH model generates a conditional variance covariance matrix, which in turn is used to generate time-varying pairwise correlations between each of the four-price series. The general DCC-MGARCH model is:

$$\varepsilon_t = H_t^{1/2} v_t$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \qquad (2.2)$$

The model specifies a $K \times 1$ vector of mean equation residuals, ε_t, as a function of a time-varying $K \times K$ conditional covariance matrix[5], H_t, and a $K \times 1$ stochastic process vector, v_t. The conditional covariance matrix is comprised of a $K \times K$ conditional variance matrix, D_t, and a $K \times K$ conditional quasicorrelation matrix, R_t. More specifically, D_t and R_t can be defined as [6]:

$$D_t = \begin{pmatrix} h_{w,t}^2 & 0 & 0 & 0 \\ 0 & h_{c,t}^2 & 0 & 0 \\ 0 & 0 & h_{e,t}^2 & 0 \\ 0 & 0 & 0 & h_{g,t}^2 \end{pmatrix} \quad \text{and,} \quad R_t = \begin{pmatrix} 1 & \rho_{wg,t} & \rho_{we,t} & \rho_{wg,t} \\ \rho_{cw,t} & 1 & \rho_{ce,t} & \rho_{cg,t} \\ \rho_{ew,t} & \rho_{ec,t} & 1 & \rho_{eg,t} \\ \rho_{gw,t} & \rho_{gc,t} & \rho_{ge,t} & 1 \end{pmatrix}$$

$$\text{where,} \quad R_t = Q_t^{\circ -1/2} Q_t Q_t^{\circ -1/2} \qquad (2.3)$$

The diagonal elements of the D_t matrix, $h_{i,t}^2$, are the conditional variances of each price change series at period t. Of importance to this analysis will be the off-diagonal elements of the R_t matrix, which are the quasicorrelations between each price change series at period t. For example,

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[5] $H_t^{1/2}$ can be obtained by performing a Cholesky factorization of H_t.

[6] Note that the variances follow a traditional univariate GARCH (1,1) process with the following form: $\sigma_{i,t}^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2$

$\rho_{we,t}$ is the estimated quasicorrelation coefficient between wheat and ethanol in period *t*; where subscripts *g* and *c* represent gasoline and corn, respectively. In this case, Q_t° is a $K \times K$ diagonal matrix of Q_t. The quasicorrelations are calculated using Equation 2.3, and an explanation of the calculation is presented in Appendix 1. The dynamics of the quasicorrelations in R_t are determined more specifically as:

$$Q_t = (1 - \lambda_1 - \lambda_2)\bar{Q} + \lambda_1 \tilde{\varepsilon}_{t-1} \tilde{\varepsilon}'_{t-1} + \lambda_2 Q_{t-1} \tag{2.4}$$

Equation 2.4 suggests that the time-varying quasicorrelations are determined by two estimated parameters[7], λ_1 and λ_2, a $K \times 1$ vector of standardized residuals, $\tilde{\varepsilon}_{t-1}$, a $K \times K$ covariance matrix of standardized errors, $\bar{Q}$, and its lagged values, Q_{t-1}. Combining the VECM mean specification with the DCC-MGARCH process yields the following general model:

$$\triangle p_t = \alpha + \sum_{i=1}^{j} \Gamma_i \triangle p_{t-i} + \Pi p_{t-1} + \varepsilon_t \tag{2.5}$$

$$\varepsilon_t = H_t^{1/2} v_t,\ v_t \sim i.i.d\ (0,1) \tag{2.6}$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{2.7}$$

Equation 2.5 is the VECM as described in Equation 2.1. Equation 2.6 represents the error process of the VECM, which follows a DCC-MGARCH process, and is a function of the time-varying conditional covariance matrix in Equation 2.7. Matrix forms of Equations 2.5, 2.6, and 2.7, where $K = 4$ and $r = 1$, are presented in Appendix 2 as, respectively, Equations 2.5.1, 2.6.1 and 2.7.1.

[7] A general requirement for the DCC specification of GARCH is that $0 \leq \lambda_1 + \lambda_2 < 1$.

2.3 Data and Preliminary Tests

The data for all markets are weekly from July 4th, 2008 to April 27th, 2018. The Canadian wheat data are CW Feed Wheat, Track Thunder Bay, measured in USD$/tonne (Qiu n.d.). The Canadian wheat prices are converted to US prices using exchange rates from the Federal Reserve Economic Data (Board of Govenors of the Federal Reserve System (US) 2020). For the rest of the time series, US data is used as indicators of global prices. The ethanol data are spot prices from Chicago and are measured in US$/gallon (Thomson Reuters n.d.). This ethanol is first-generation, made from corn and soybeans. The corn data are spot prices of Chicago Yellow Corn No. 2 measured in USD$/bushel (Global Financial Data n.d.). Gasoline prices are measured in USD$/gallon (Energy Information Administration n.d.). The general summary statistics of each of the price series are presented in Table (2-1). The coefficients of variation (CV) suggest that ethanol and wheat prices are the least volatile, while corn prices are the most volatile.

Table 2-1: Summary Statistics of Prices (n=513)

Price	Mean	Std. Dev.	CV	Minimum	Maximum
Wheat (USD$/tonne)	185.96	46.11	0.25	124.74	309.17
Corn (USD$/bushel)	4.67	1.56	0.33	2.63	8.45
Ethanol (USD$/gallon)	1.96	0.47	0.24	1.22	3.72
Gasoline (USD$/gallon)	2.16	0.63	0.29	0.84	3.36

The price series in Figure (2-1) tend to display similar patterns. All price series experience a similar peak in 2008, which could have been the result of low global crop yields in 2006-2007, high oil prices, and a growing demand in corn and maize for biofuel production (Trade and Markets Division of FAO 2009; Abbott et. al. 2008; Trostle 2008; Mitchel 2008). High prices in all markets from 2010 to 2012 can be attributed to factors like those that caused high prices in 2008 (Coulibaly

2013). Wheat and corn prices fell dramatically in 2013. This may have been a result of agricultural prices adjusting to (1) lower than average corn yields from 2010 to 2013, which were exacerbated by a US drought that caused poor corn yields in 2012, and (2) above-average US corn yields since 2013 (Bureau of Labor Statistics 2012; Schnitkey 2019). Ethanol prices tended to be volatile in 2013, and may have been reacting to the aforementioned price changes in the corn market. Furthermore, as the US approached the ethanol-gasoline E10 blend wall in 2013-2014, policy uncertainty from the Environmental Protection Agency (EPA) regarding future ethanol demand may have affected ethanol price volatility (Baumeister et al. 2017; Knittel et al. 2015). US ethanol prices then declined substantially in 2014 and have remained low since. Irwin (2019) finds that the low ethanol price since 2014 is a result of rising US ethanol production since 2014, and not a result of a change in ethanol demand (Irwin 2019). Gasoline prices decreased dramatically from 2014 to 2015. This was likely a result of low oil prices caused by stagnant oil demand and increased supply (Prest 2018; Baumeister and Kilian 2016).

Preliminary tests are conducted on the logged price series and the price change series to identify a suitable approach to modeling the mean process. First, Augmented Dicky-Fuller (ADF) tests and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are conducted on each of the logged price series to test whether the series are stationary or non-stationary. The test statistics and corresponding significance levels are presented in Table (2-2). The absolute values of the test statistics from the ADF tests for all the logged price series were smaller than the 10% critical value. Therefore, the null hypothesis that the logged price series are non-stationary is not rejected. The absolute values of the test statistics from the KPSS tests for all the logged price series were larger than the 1% critical value. Therefore, the null hypothesis that the logged prices are trend stationary is rejected.

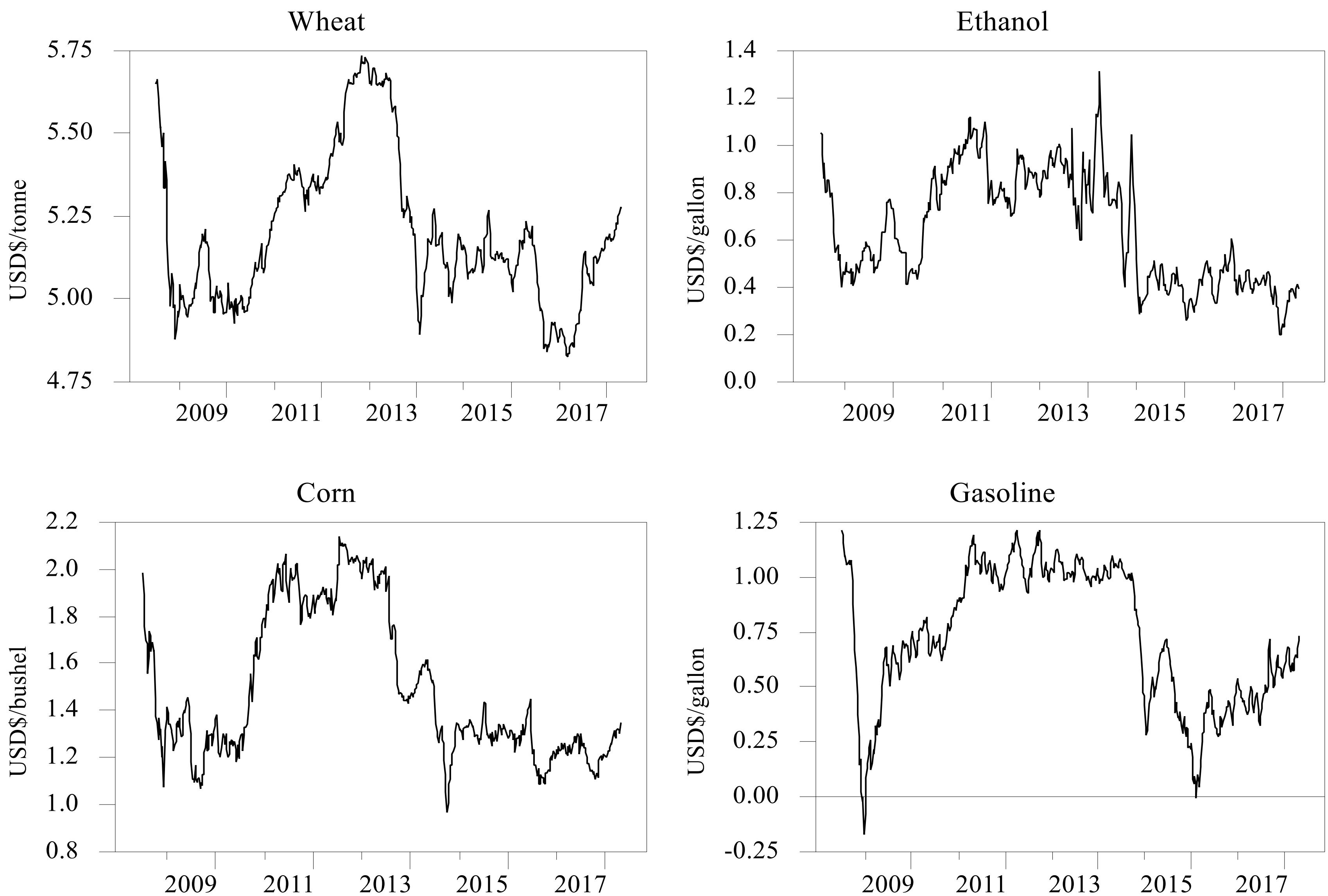

Figure 2-1: Canadian Wheat and US Corn, Ethanol, and Gasoline Prices

Table 2-2: Unit Root Test Statistics

	Wheat	Corn	Ethanol	Gasoline
ADF				
None	-0.642	-1.02	-1.46	-1.23
Drift	-2.35	-2.01	-2.73	-2.32
Drift & Trend	-2.17	-1.92	-2.93	-2.22
KPSS	1.25**	1.57**	1.52**	1.49**

* Significant at the 5% level.
** Significant at the 1% level.

Next, the logged price series are first-differenced to obtain price changes and the ADF tests are conducted again. The results suggest that each price change series is stationary of order one.[8] Therefore, the mean process is modeled with the log-differenced prices (i.e. price changes). Table (2-3) shows the summary statistics for the price change series.

Table 2-3: Summary Statistics of Price Changes, (n=513)

Price Change	Mean	Std. Dev.	Minimum	Maximum
Wheat (%Δ USD$/tonne)	-0.0007	0.030	-0.18	0.084
Corn (%Δ USD$/bushel)	-0.0012	0.045	-0.200	0.220
Ethanol (%Δ USD$/gallon)	-0.0015	0.053	-0.330	0.236
Gas (%Δ USD$/gallon)	-0.0012	0.042	-0.173	0.165

Figure (2-2) shows the series of price changes for the four products and suggests that there may be similar periods of high and low-price change volatility across the series that generally correspond to periods of rising and falling prices described above.

[8] The absolute values of the test statistics from the ADF tests for all series were larger than the 1% critical value. [8] Therefore, the null hypothesis of a unit root process for all price change series is rejected.

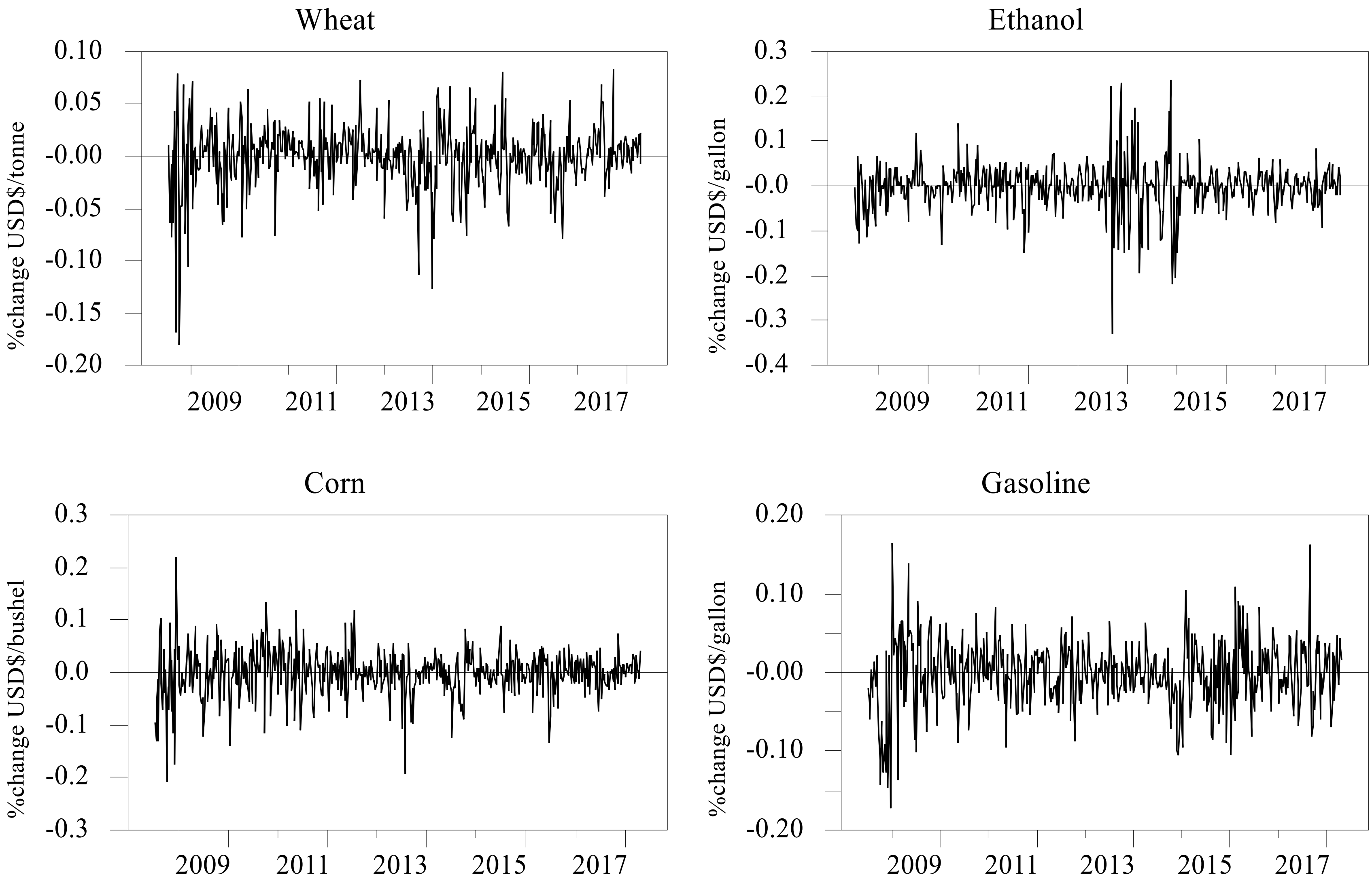

Figure 2-2: Canadian Wheat and US Corn, Ethanol, and Gasoline Price Changes

2.4 Results

The Engle-Granger cointegration test suggests that there is a statistically significant cointegrating relationship between the logged price series at the five-percent level.[9] Next, a Johansen cointegration test is carried out to investigate whether there are more than one statistically significant cointegrating relationship between the logged price series.[10] The results of these tests are presented in Table (2-4). The test statistics for the trace test and eigenvalue test are statistically insignificant when the null hypothesis is that there is at most one cointegrating relationship (i.e. $r \leq 1$). This result suggests that the null hypothesis of there being at most one cointegrating relationship is not rejected. Therefore, the price series can be modelled simultaneously using a VECM with one cointegrating relationship.

Table 2-4: Johansen Test for Cointegration

Null Hypothesis	*Eigenvalue Test Statistics*	*Trace Test Statistics*
$r = 0$	41.12***	69.68***
$r \leq 1$	17.54	28.56
$r \leq 2$	7.14	11.02
$r \leq 3$	3.88	3.88

* Significant at the 10% level.
** Significant at the 5% level.
***Significant at the 1% level.

[9] The value of the test statistic was larger than the 5% critical value. Therefore, the null hypothesis that the price series are not cointegrated is rejected.
[10] The Johansen cointegration test requires a defined lag structure. The AIC criterion is first used to determine the optimal lag-length for the underlying auto-regressive process for each series. The optimal length was found to be two lags.

Along with the Johansen cointegration test, the coefficients for the error correction process are estimated and found to be statistically significant at the five-percent level. The long run cointegrating equation is:

$$p_{w,t} = 1.07p_{c,t} - 1.20p_{e,t} + 0.48p_{g,t} \tag{2.8}$$

Because the estimated cointegrating vector is normalized to wheat, the parameters indicate how each price affects wheat prices in the long run, *ceteris paribus*. [11] For example, a 1% increase in the long-run corn price is associated with a 1.07% increase in the long run wheat price.

Next, the full VECM is estimated. Several notable results are presented in Table (2-5). First, corn prices do not react to lagged price changes. This result is consistent with prior studies, which have noted that changes in other agricultural and energy markets appear to have little to no short run effect on the large US corn market (Etienne et al. 2017; Trujillo-Barrera et.a 2012). Specifically, Trujillo-Barrera et. al (2012) note that since corn supply can be reallocated from conventional uses (i.e. animal feed, food) to ethanol use, the US corn market is able to withstand short run demand shocks in the ethanol market. Instead, short-run price dynamics in US corn markets tend to be driven by weather and growing conditions, government policies, and macroeconomic factors (Abbott and Battisti 2011). Second, corn price changes have a significant effect on the other three markets. For example, a 1% change in corn prices in the current period is estimated to change ethanol prices in the next period by about 0.16%. Third, wheat and gasoline price changes tend to be affected by their own lagged price changes. For example, a one percent change in wheat prices in the current period is estimated to change wheat prices in the next period by 0.11%. Finally, there are statistically significant long run price relationships that are reflected

[11] All the estimated parameter effects have a *ceteris paribus* interpretation.

in the estimated error-correction parameters (ECPs). Wheat and ethanol prices respond to deviations in their long run equilibrium values, while corn and gasoline do not. This result suggests that gasoline and corn prices are exogenous to the long run system. Specifically, following a shock to the long-run system, wheat and ethanol prices are estimated to adjust back to the long run relationship at a rate of 3.5% and 7.3% per week, respectively.

Table 2-5: VECM Results

Wheat Equation		Corn Equation		Ethanol Equation		Gas Equation	
Variables	Coeff.	Variables	Coeff.	Variables	Coeff.	Variables	Coeff.
Constant	0.141***	Constant	0.001	Constant	0.30***	Constant	0.025
Wheat (-1)	0.11**	Wheat (-1)	-0.008	Wheat (-1)	0.029	Wheat (-1)	0.001
Corn (-1)	0.070**	Corn (-1)	-0.013	Corn (-1)	0.157***	Corn (-1)	0.126***
Ethanol (-1)	0.017	Ethanol (-1)	0.037	Ethanol (-1)	0.048	Ethanol (-1)	0.036
Gas (-1)	-0.020	Gas (-1)	-0.027	Gas (-1)	0.014	Gas (-1)	0.238***
ECP	-0.035***	ECP	-0.000	ECP	-0.073***	ECP	-0.006

Note: (-1) indicates that the variable has been lagged by one period.

ECP is the estimated error correction parameter of the error correction model.

* Significant at the 10% level.
** Significant at the 5% level.
***Significant at the 1% level.

An important assumption about the validity of the VECM is that the errors follow a homoscedastic process. Therefore, a closer look at the VECM residuals is warranted. The model residuals for each price series are presented in Figure (2-3). There appears to be similar periods of high residual volatility across the series that generally correspond to the periods of rising and falling prices described in Section 2.3. This observation suggests that there may be autocorrelation in the model residuals. An ARCH-LM test is performed on the VECM residuals and find that autocorrelation is statistically significant. The results of the ARCH-LM test validate the decision to model the VECM with a DCC-MGACRH process [12].

Next, the DCC-MGARCH model is estimated as a system with the mean VECM equation. The mean equation results in Table (2-6) are like the results in Table (2-5), in that the statistical significance of the price change transmission effects and the error correction parameters (ECPs) remain the same. The one exception is that the effect of corn in the wheat equation is no longer significant. The ECPs now indicate that if there is a shock to the equilibrium relationship between prices, wheat and ethanol prices adjust back to the long run relationship at a rate of 2.8% and 4.3% per week, respectively. The difference between the estimated adjustment speeds in the VECM-DCC-MGARCH means equation and the simple VECM equation is that the deterministic disturbances to the price changes are now being picked up by the DCC volatility model component.

One means of investigating whether the use of a DCC-GARCH specification is appropriate is to test whether the lambda parameters satisfy the general constraint, $0 \leq \lambda_1 + \lambda_2 < 1$. The sum of the estimated lambda parameters was equal to 0.95 and statistically significant at the 1% level. Therefore, the DCC specification is supported. An ARCH-LM test is performed on the VECM-DCC-GARCH system residuals, and the test fails to reject the null hypothesis that there is no serial correlation.

[12] The value of the test statistic was larger than the 1% critical value. Therefore, the null hypothesis that the residuals series are not serially correlated is rejected.

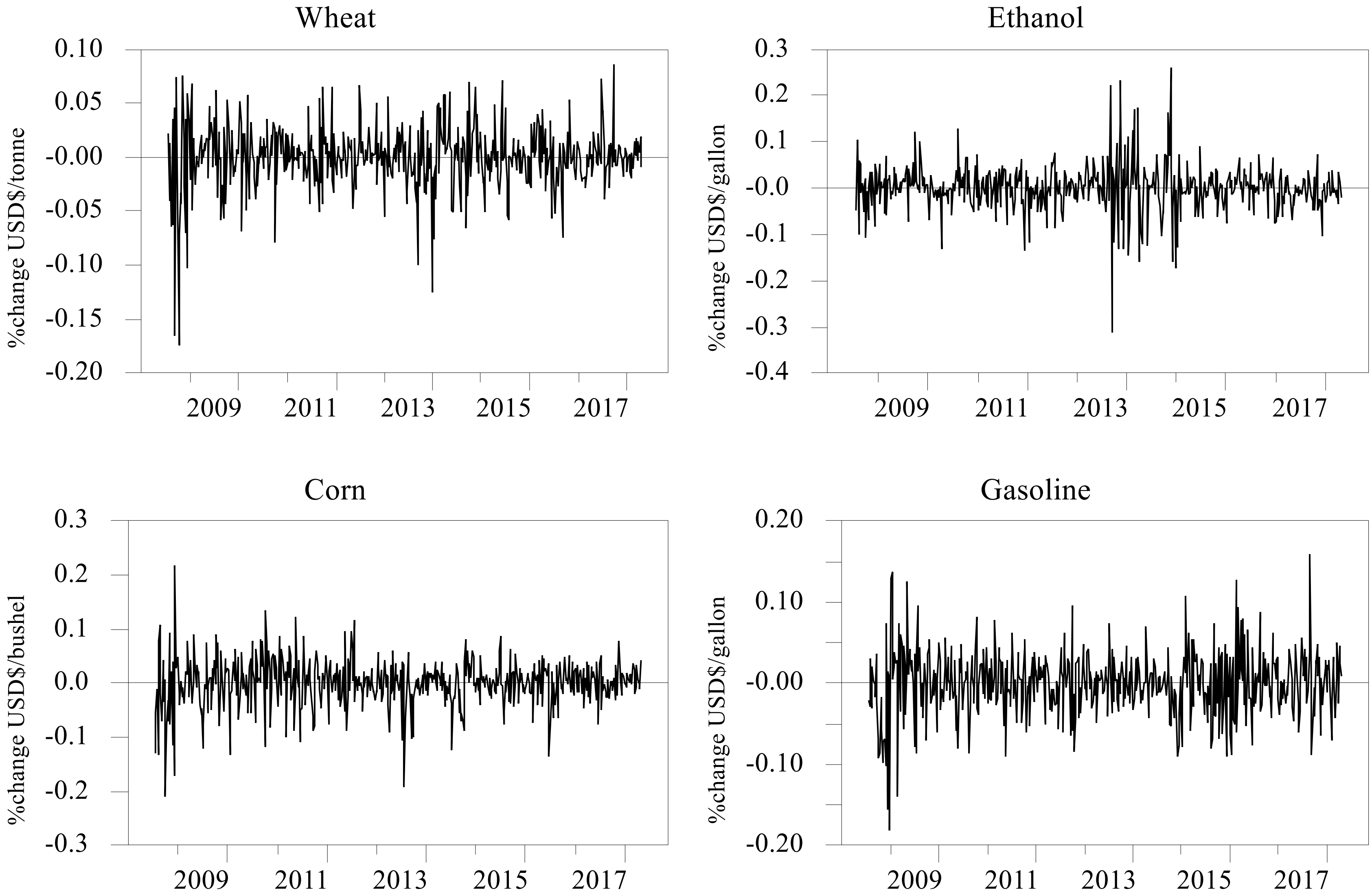

Figure 2-3: Residuals from the VECM

Table 2-6: VECM results with DCC specification

Wheat Equation		Corn Equation		Ethanol Equation		Gas Equation	
Variables	Coeff.	Variables	Coeff.	Variables	Coeff.	Variables	Coeff.
Constant	0.116***	Constant	-0.002	Constant	0.178***	Constant	-0.006
Wheat (-1)	0.147***	Wheat (-1)	0.030	Wheat (-1)	-0.030	Wheat (-1)	0.049
Corn (-1)	0.025	Corn (-1)	-0.080	Corn (-1)	0.147***	Corn (-1)	0.084**
Ethanol (-1)	0.020	Ethanol (-1)	0.018	Ethanol (-1)	0.027	Ethanol (-1)	0.002
Gas (-1)	-0.035	Gas (-1)	-0.056	Gas (-1)	0.023	Gas (-1)	0.239***
ECP	-0.028***	ECP	0.000	ECP	-0.043***	ECP	-0.001

* Significant at the 10% level.
** Significant at the 5% level.
***Significant at the 1% level.

Table (2-7) reports the estimated ARCH and GARCH coefficients. The ARCH and GARCH parameters measure the vulnerability and persistency of the conditional price change volatilities, respectively. Persistency is the extent to which price change volatility in the previous period affects price change volatility in the current period. The values of the estimated GARCH parameters for each equation are close to 1, which means that price change volatility in each market is highly persistent. Vulnerability is the extent to which price change shocks in the previous period affect price change volatility in the current period. The individual ARCH parameters for each equation are statistically significant, which implies that current price change volatility is somewhat vulnerable to price change shocks from the previous period.

Table 2-7: VECM-DCC Volatility Equation

Equation	Constant	ARCH	GARCH
Wheat	0.00***	0.144***	0.755***
Corn	0.00***	0.165***	0.760***
Ethanol	0.00***	0.159***	0.750***
Gasoline	0.00**	0.105***	0.850***

* Significant at the 10% level.
** Significant at the 5% level.
***Significant at the 1% level.

Figure (2-4) shows the dynamic correlation coefficients, which indicate how wheat, corn, ethanol, and gasoline markets are interdependent. First, all pairwise market relationships are positive from 2008 to 2018; as price changes in one market increase (decrease), the price changes in another market increase (decrease). Second, some market relationships tend to be more sensitive to periods of significant economic events than others. For example, the pairwise relationships between wheat and gasoline and corn and gasoline tend to peak during the 2008-2009 financial crisis period, while the relationship between ethanol and gasoline does not. The relationship between wheat and ethanol tends to become quite volatile during 2013-2014. From 2014-2015, ethanol and gasoline markets become less correlated, while corn and ethanol markets become more correlated. Once again, the periods that are associated with changes to market relationships coincide with the periods of rising and falling prices described in Section 2.3. Third, there does not appear to be long run trends in the pairwise correlations; each pairwise market relationship remains relatively flat from 2008 to 2018.

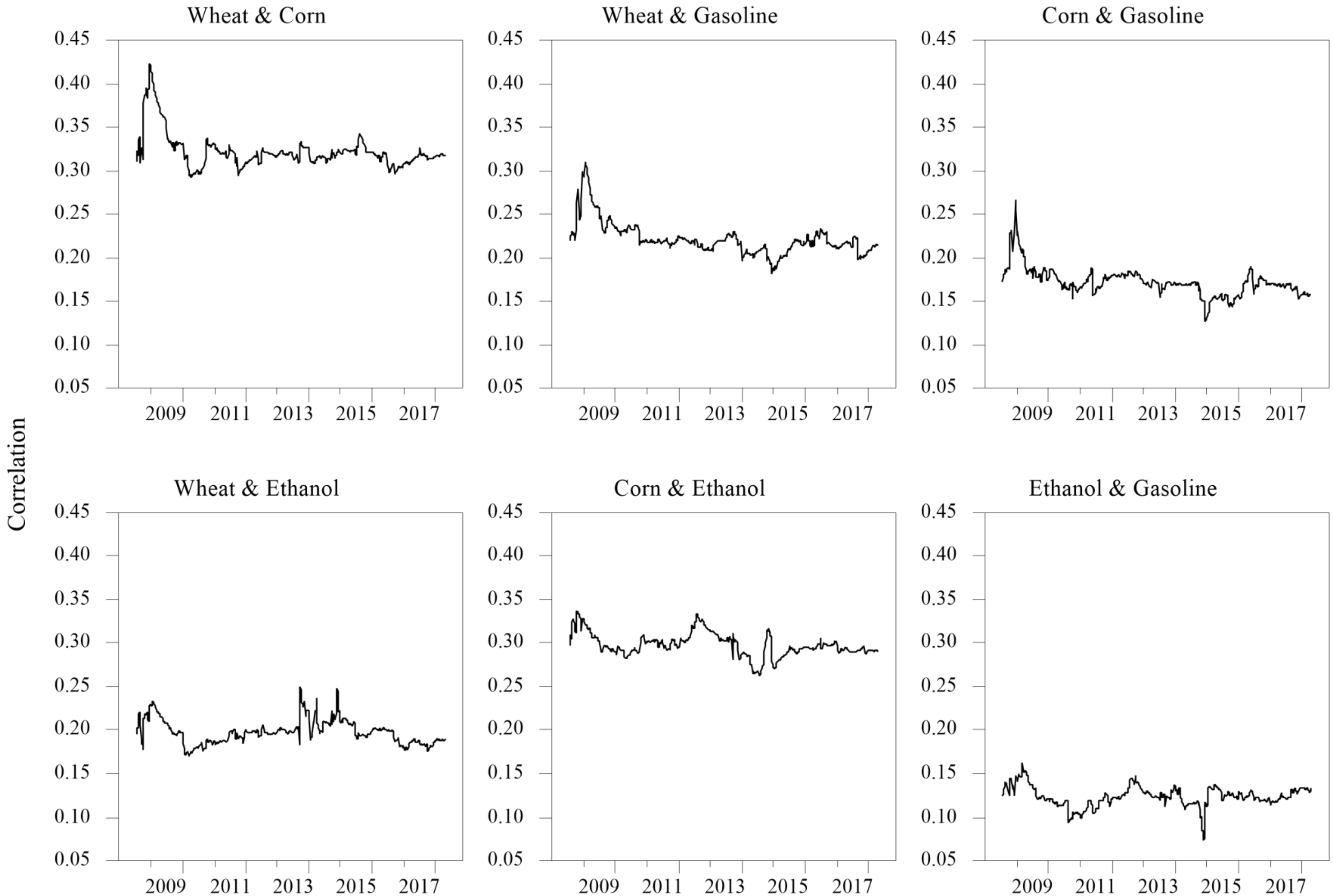

Figure 2-4: Dynamic Correlation Coefficients

Following the results of Figure (2-4), there appears to be a logical flow to the order of strongest to weakest market relationships. The order of the strength of the mean pairwise correlations is presented in Figure (2-5). The average correlations between the two agricultural commodity prices (i.e. wheat and corn) is the strongest. Similar vulnerability to weather conditions, costs of farm inputs, demand for food in developing countries, and livestock feed market demand may explain why wheat and corn markets are correlated (Trostle 2008). The second strongest relationship is between ethanol and the energy feedstock, corn. One would expect there to be a strong relationship between the corn and ethanol markets; the ethanol industry is the largest value-added market for corn growers in the US, with corn accounting for ninety-six percent of feedstock used to produce ethanol in the US from 2011 to 2017 (Renewable Fuels Association 2019). The third, fourth, and fifth strongest pairwise market relationships are between agricultural and energy markets that do not have a feedstock relationship. Finally, the weakest pairwise market relationship is between energy and ethanol energy markets. One explanation for this result may be due to blending mandates and blending constraints in the US. Irwin and Good (2016) suggest that the demand curve for ethanol is inelastic due to volume mandates and the E10 blend wall. The market price of ethanol, which is the intersection point of the ethanol supply and demand curve, has been typically less than the equilibrium price of gasoline since 2007. Therefore, any observed changes to gasoline prices when the price of gasoline is higher than the price of ethanol does not result in changes to ethanol prices.

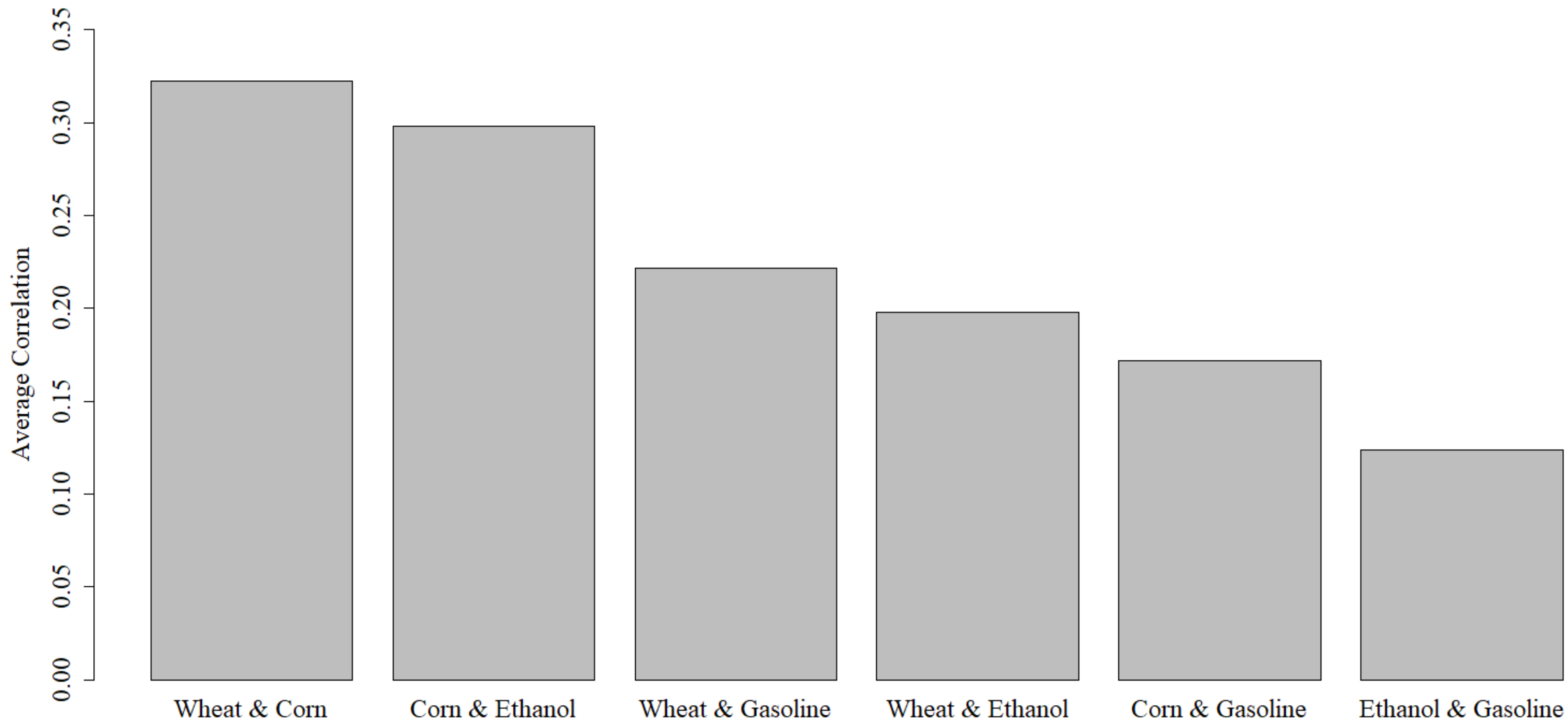

Figure 2-5: Average Dynamic Correlation Coefficients

2.5 Discussions and Conclusions

There is an extensive body of recent time series literature that has explored relationships among agricultural and energy prices. The general motivation for these analyses is to understand how the recent growth in global biofuel and energy production has affected food prices and food price volatility (Filip et al. 2019; Hochman and Zilberman 2016). Little work has been done to investigate how agricultural and energy price relationships may affect the development of a second-generation ethanol industry that could use agricultural residues as a feedstock.

Prospective Canadian second-generation ethanol producers will only invest in ethanol production operations if it is profitable to do so, which could depend heavily on future prices. Even though time series price data for second-generation feedstock prices (i.e. wheat straw prices) is unavailable, wheat grain prices are likely correlated to the supply of wheat straw since straw is a by-product of wheat. Therefore, this analysis has investigated the relationships between prices related to the first-generation ethanol industry (i.e. Canadian wheat, US corn, ethanol, and gasoline), in order to gain insights into future price scenarios that may influence whether a second-generation ethanol industry could emerge in Western Canada. There are several important takeaways from the results.

2.5.1 Results from VECM Analysis

As a precursor to the VECM analysis, a Johansen cointegration test was used to identify if an equilibrium relationship exists between the four markets under consideration. A long run relationship between all markets is identified. This result implies some degree of predictability regarding future prices that will affect first and second generation ethanol producers.

The VECM results reflect the short run price dynamics in each market. Corn price changes are not affected by price changes in any of the other markets. However, ethanol and gasoline price changes are found to respond in following periods to corn price changes. This is reflective of corn being the primary feedstock of ethanol in the US, and of ties between ethanol and gasoline. The short-run relationship between corn and ethanol is a mixed result for first and second-generation ethanol producers. First-generation ethanol producers can pass along higher feedstock prices to blenders in the form of higher ethanol prices, and second-generation ethanol producers can benefit from the higher ethanol prices. On the other hand, a decrease to corn prices means that ethanol prices follow.

Short-run price changes in the ethanol market are also dictated by shocks to the equilibrium price relationship. This would have financial implications for first and second-generation producers. First generation ethanol producers may experience lower profits (if ethanol prices decrease relative to corn prices) or higher profits (if ethanol prices increase relative to corn prices) in the short-run. However, in the long run ethanol prices tend to return to the equilibrium level with the other prices. Similarly, second-generation ethanol producers may experience higher profits (if ethanol prices increase), or lower profits (if ethanol prices decrease).

Short-run price changes in the wheat market are also dictated by shocks to the equilibrium price relationship, which could have financial implications for a second-generation ethanol industry. A positive (negative) shock to the equilibrium system that causes wheat prices to adjust to a higher (lower) equilibrium price may encourage farmers to grow wheat more (less) frequently. In turn, there may be more (less) wheat straw available for ethanol production. However, in the long run wheat prices return to the equilibrium level with the other prices. Because short-run price dynamics may affect the variability of output prices and feedstock supply, investors and policy makers could consider strategies that counteract unfavourable price changes to wheat and ethanol caused by changes to their relationship with the corn and gasoline markets.

2.5.2 Volatility Vulnerability and Persistency from DCC GARCH Results

The significant ARCH estimates suggest that price change shocks can create price change volatility in each market, and the estimated GARCH parameters suggest that volatility in each market persists. Specifically, ethanol and wheat price change volatility persist for approximately 16 weeks after a shock occurs. This result suggests the need for prospective ethanol producers to adopt management approaches that can adapt to wheat and ethanol price change volatility that does not quickly disappear.

2.5.3 Dynamic Market Interdependence from DCC GARCH Results

The estimated dynamic correlations suggest that market pairs move together with relatively constant relationships over time. All pairwise relationships were relatively strong in 2008 and 2009 (during the financial collapse) compared to other years. This result is consistent with other studies that have found strong relationships between agriculture and energy markets during the financial crisis period (Ji 2012; Bonato 2019; Büyükşahin and Robe 2014). Pairwise relationships involving ethanol tended to be volatile in 2013-2014, when agricultural prices were volatile and US ethanol production approached the E10 blend wall. This information suggests that major disruptions to the economy simultaneously influence several markets that are important to second-generation ethanol producers, indicating the need for producers to adopt risk management strategies that counter such disruptions.

The weakest pairwise correlation was estimated between ethanol and gasoline. This result is good news for first and second-generation ethanol producers, because it suggests that notoriously fluctuating gasoline prices do not transmit into changing ethanol prices. Stronger correlations are associated with the US corn market and its relationships with wheat and ethanol. This result is bad news for first and second-generation producers, because it suggests that the second-generation feedstock supply and output price of ethanol follow changes to the US corn price.

The strong relationships between wheat and corn and ethanol and corn may partly explain why a significant relationship was identified between wheat and ethanol. An increase (decrease) to ethanol prices may be associated with an increase (decrease) to wheat prices, which may increase (decrease) wheat production and the supply of wheat straw. Therefore, a second-generation ethanol producer could be in an environment of (a) high output prices and high feedstock supply, or (b) low output prices and low feedstock supply. In situation (a), producers may not be able to take advantage of high output prices by increasing production, since increasing output capacity would likely be unattainable in the short run due to capacity constraints. In situation (b) a second-generation ethanol producer would most likely cut their production due to low output prices. A unique hedging strategy for second-generation producers could involve buying excess straw when ethanol prices and straw supply is high in situation (a), and then selling straw reserves to alternative markets when ethanol prices are low in situation (b).

It is important to note that the structure of relationships between markets may change as new markets develop. Therefore, future research may consider investigating how these relationships change, to understand the conditions under which a second-generation ethanol industry could be financially sustainable.

Chapter 3: Price Volatility Spillovers Between Canadian Wheat and US Energy and Agricultural Commodities

3.1 Introduction

Investments in second-generation ethanol production require information about future price movements, because input and output price dynamics are used by ethanol producers to formulate business plans and risk management strategies (The Clean Fuels Development Coalition and The Nebraska Ethanol Board 2006). Significant volatility of ethanol and feedstock prices may be a significant barrier to entry for prospective second-generation ethanol producers. Therefore, the purpose of this paper is to identify price transmissions and volatility spillovers between prices related to the first-generation ethanol industry: Canadian wheat prices and US ethanol, corn, and gasoline prices. The price of wheat grain may affect the production of wheat, which in turn may affect the availability of wheat straw as a second-generation ethanol feedstock. The US corn market is related to wheat as an agricultural commodity and is related to ethanol as a first-generation feedstock. Gasoline is related to both wheat and corn as an input to production because the grains are used to make ethanol that is mixed with gasoline.

A large body of literature uses cointegration and multivariate general autoregressive conditional heteroskedasticity (MGARCH) analyses to investigate price and price volatility transmission between agricultural and energy markets (Serra and Zilberman 2013). The literature identifies significant, and often bi-directional, spillover effects between agricultural and energy markets (Balcombe and Rapsomanikis 2008; Busse, Brummer and Ihle 2012; Cabrera and Schulz 2016; Campiche et al. 2007; Chang, Li and McAleer 2015; Chang, Liu and McAleer 2019; Du, Yu and Hayes 2011; Dutta and Noor 2017; Serra 2013; Serra, Zilberman and Gil 2011; Walters

2018; Xiarchos and Burnett 2018; Zhang et al. 2008). For example, Serra (2011) finds that crude oil and sugar prices affect ethanol prices, and that crude oil and sugar price volatility affects ethanol price volatility. Likewise, Trujillo-Barrera, Mallory and Garcia (2012) find that corn prices affect ethanol prices and that crude oil market volatility affects corn and ethanol market volatility.

An extension of the agricultural and energy spillover literature studies how energy policy announcements have affected price and volatility transmissions between agricultural and energy markets. In general, this literature finds that the volatility relationships between energy and agricultural markets tend to increase because of changes to energy policies (Mensi et al. 2014; Karali 2012; Demirer, Kutan and Shen 2012; Gardebroek and Hernandez 2013). For example, Serletis and Xu (2019) find that the adoption of the Energy Independence and Security Act in 2007 strengthened the volatility transmission relationship between crude oil prices and soybean, corn, and sugar prices. Likewise, Herwartz and Saucedo (2020) analyze changes in volaility transmission relationships between crude oil, corn, wheat, sugar, soybean, and palm oil prices from 1995 to 2015. The authors find that the volatility spillovers from the crude market to the biofuel feedstock markets intensified during periods of changing ethanol production mandates and tax credits to US fuel blenders.

A similar extension of the volatility spillover literature investigates how international economic crises, most notably the 2008 financial crisis, affected price and volatility transmissions between agricultural and energy markets. The general conclusion from this literature is that economic crises strengthen price volatility relationships between markets. (Ji and Fan 2012; Kang, McIver and Yoon 2017; Lu, Yang and Liu 2019; Vivian and Wohar 2012). For example, Kang et al. (2019) find significant bi-directional volatility spillovers between crude oil, corn, soybean, and wheat futures prices during the 2008-2009 financial crisis. In the post crisis period, there were no observed volatility spillovers from the crude oil market to the agricultural markets.

The existing literature has produced evidence that international agricultural and energy market volatility relationships are significant, and that these relationships may change over time. This analysis adds value to the literature by identifying whether volatility relationships exist between the Canadian wheat market and international corn and energy markets. This research may be used to inform future price scenarios that can help to develop relevant government policies and investment strategies that may be used to develop a second-generation ethanol industry in Western Canada that uses wheat residues as a feedstock.

In the next section the econometric approaches are presented, and Section 3.3 discusses the data used. In Section 3.4, structural break tests are conducted on preliminary model results and a new model with time dummies is presented. Section 3.5 presents the final model results, and Section 3.6 presents the conclusions of the analysis and discusses the implication of the results.

3.2 Methods

The time-series analysis consists of estimating mean and volatility equations together as a system. First, Engle-Granger (Engle and Granger 1987) and Johansen cointegration tests (Johansen 1991) are used to identify long-run relationships between each of the price series. Once the cointegrating equations have been identified, a vector error-correction model (VECM) is employed to model the short run and long run relationships between each of the price series. The volatility equation component of this system is a MGARCH model with a Baba-Engle-Kraft-Kroner (BEKK) specification. The BEKK MGARCH model is used because the purpose of this paper is to identify volatility spillover effects between Canadian wheat prices and US corn, ethanol, and gasoline prices. The mean VECM equation and the DCC-MGARCH volatility component are estimated as a system using the maximum likelihood method.[13]

3.2.1 Conditional Mean Specification

An Engle-Granger cointegration test is employed to identify whether a long-run relationship exists between the Canadian wheat and US corn, ethanol, and gasoline markets. The Engle-Granger cointegration test is a two-stage process that begins by regressing a dependent variable, in this case wheat prices, on the independent variables, in this case corn, ethanol, and gasoline prices. Then, the first differenced residuals are regressed on the lagged level of the residuals. The null hypothesis is that the residuals are not stationary, which implies that the price series are not cointegrated and follow unit root processes (i.e. the estimated coefficients on the lagged residuals are equal to one). The alternative hypothesis is that the residuals are stationary and therefore the price series are cointegrated. If the price series are found to be cointegrated, they can be modelled with a VECM.[14] The general VECM specification is:

$$\triangle p_t = \alpha + \sum_{i=1}^{j} \Gamma_i \triangle p_{t-i} + \Pi p_{t-1} + \varepsilon_t \tag{3.1}$$

$$Where, \qquad \Pi p_{t-1} = \theta(\mu' p_{t-1})$$

In this analysis, $\triangle p_t$ is a $K \times 1$ vector of price changes (i.e. percent change in price) in period, *t*, where *K* is the number of markets considered in this analysis (i.e. four). The α is a $K \times 1$ vector of constants and ε_t is a $K \times 1$ vector of residuals. The VECM considers the short and long-run relationships between each market. The short-run effects are captured by, Γ_i, which is a $K \times K$

[13] The Berndt-Hall-Hall-Hausman (BHHH) algorithm is used to estimate the BEKK-MGARCH system.

[14] Before the VECM model is estimated, an Engle Granger test and a Johansen cointegration test are performed in Section 4 to specify the mean equation.

matrix of estimated parameters on the $K \times 1$ vector of lagged price changes, Δp_{t-i}. The long-run effects are captured by the error-correction process, Πp_{t-1}. The $K \times K$ coefficient matrix, Π, is a function of a $K \times r$ matrix[15] of error-correction parameters, θ, and the transpose of a $K \times r$ cointegrating equation matrix, μ. The matrix operation $\mu' p_{t-1}$, where p_{t-1} is a $r \times K$ matrix of lagged prices, will yield a $r \times 1$ vector of cointegrating equations. Each element of the estimated $K \times r$ vector of parameters on the error-correction process, θ, can be interpreted as the speed at which the respective dependent variable adjusts to a deviation in the long run equilibrium relationship.

3.2.2 Volatility Model Specification

A GARCH process models the relationship between the variance of the residuals from a mean equation, σ_t^2, as a function of lagged residuals, ε_{t-m}^2, and lagged variance, σ_{t-k}^2 (Bollerslev 1986). Equation 3.2 is the general univariate GARCH model:

$$\sigma_t^2 = C + \gamma_1 \varepsilon_{t-1}^2 \ldots + \gamma_m \varepsilon_{t-m}^2 + \delta_1 \sigma_{t-1}^2 + \cdots + \delta_k \sigma_{t-k}^2 \qquad (3.2)$$

In Equation 3.2, the γ_m parameters are the estimated ARCH parameters, and the δ_k parameters are the estimated GARCH parameters. The general univariate GARCH model can be extended to a multivariate case. The simplest MGARCH representation is the diagonal VECH (DVECH) model (Bollerslev, Engle and Woolridge 1988). The unrestricted VECH, or full VECH, is rarely used in applied MGARCH estimation because it is computationally demanding and suffers from the curse of dimensionality if there are more than two variables. An important characteristic of the DVECH model is that the Hadamard product of the ARCH and GARCH parameter matrices ensures that each element in the variance covariance matrix is only affected by

[15] The *r* dimension represents the number of cointegrating vectors.

its own past values, and by the past values of the ARCH terms. The model does not allow for cross covariance effects. For this paper, another restricted specification of the full VECH model that allows for cross effects is explored: the BEKK specification (Engle and Kroner 1995). Specifically, the general BEKK model can be represented as:

$$\varepsilon_t = H_t^{1/2} v_t,$$
$$H_t = CC' + \sum_{k=1}^{K} \sum_{i=1}^{p} A'_{ik} \varepsilon_{t-i} \epsilon'_{t-i} A_{ik} + \sum_{k=1}^{K} \sum_{i=1}^{q} B_{ik} H_{t-j} B'_{ik} \tag{3.3}$$

The model specifies a $K \times 1$ vector of mean equation residuals, ε_t, as a function of a time-varying $K \times K$ conditional covariance matrix, H_t, and a $K \times 1$ stochastic process vector, v_t. In Equation 3.3, C is a $K \times K$ upper triangular matrix of constants, A_{ik} is a $K \times K$ matrix of estimated ARCH parameters, and B_{ik} is a $K \times K$ matrix of estimated GARCH parameters. Unlike the diagonal VECH model, the BEKK specification allows for the off-diagonal elements of the variance covariance matrix, ARCH parameter matrix, and GARCH parameter matrix to be non-zero. The BEKK MGARCH model with a GARCH (1,1) representation can be expressed in general matrix form as:

$$\begin{bmatrix} \sigma_{11,t}^2 & \cdots & \sigma_{1p,t} \\ \vdots & \ddots & \vdots \\ \sigma_{k1,t} & \cdots & \sigma_{kp,t}^2 \end{bmatrix} = \begin{bmatrix} C_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ C_{k1} & \cdots & C_{kp} \end{bmatrix} \times \begin{bmatrix} C_{11} & \cdots & C_{k1} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & C_{kp} \end{bmatrix}$$
$$+ \begin{bmatrix} A_{11} & \cdots & A_{k1} \\ \vdots & \ddots & \vdots \\ A_{1p} & \cdots & A_{kp} \end{bmatrix} \times \begin{pmatrix} \epsilon_{1,t-1} \\ \epsilon_{2,t-1} \\ \vdots \\ \epsilon_{k,t-1} \end{pmatrix} \times (\epsilon_{1,t-1} \quad \epsilon_{2,t-1} \quad \cdots \quad \epsilon_{p,t-1}) \times \begin{bmatrix} A_{11} & \cdots & A_{1p} \\ \vdots & \ddots & \vdots \\ A_{k1} & \cdots & A_{kp} \end{bmatrix} \tag{3.4}$$
$$+ \begin{bmatrix} B_{11} & \cdots & B_{1p} \\ \vdots & \ddots & \vdots \\ B_{k1} & \cdots & B_{kp} \end{bmatrix} \times \begin{bmatrix} \sigma_{11,t-1}^2 & \cdots & \sigma_{1p,t-1}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{k1,t-1}^2 & \cdots & \sigma_{kp,t-1}^2 \end{bmatrix} \times \begin{bmatrix} B_{11} & \cdots & B_{k1} \\ \vdots & \ddots & \vdots \\ B_{1p} & \cdots & B_{kp} \end{bmatrix}$$

The formulations in 3.3 and 3.4 show that the BEKK representation allows the variance equations for one variable to be affected by other variables. More formally, one can imagine what the variance equations would look like in a GARCH (1,1) specification with the four markets. For example, the variance equation for wheat can be expressed as:

$$\begin{aligned}\sigma_{w,t}^2 = C_{ww}^2 &+ A_{ww}^2 u_{w,t-1}^2 + A_{cw}^2 u_{c,t-1}^2 + A_{ew}^2 u_{e,t-1}^2 + A_{gw}^2 u_{g,t-1}^2 + 2A_{1w}A_{cw}u_{w,t-1}u_{c,t-1} \\ &+ 2A_{ww}A_{ew}u_{w,t-1}u_{e,t-1} + 2A_{cw}A_{ew}u_{c,t-1}u_{e,t-1} + 2A_{ww}A_{gw}u_{w,t-1}u_{g,t-1} \\ &+ 2A_{cw}A_{gw}u_{c,t-1}u_{g,t-1} + 2A_{ew}A_{gw}u_{e,t-1}u_{g,t-1} + B_{ww}^2\sigma_{w,t-1}^2 + B_{cw}^2\sigma_{c,t-1}^2 \\ &+ B_{ew}^2\sigma_{e,t-1}^2 + B_{gw}^2\sigma_{g,t-1}^2 + 2B_{ww}B_{cw}\sigma_{wc,t-1} + 2B_{ww}B_{ew}\sigma_{we,t-1} \\ &+ 2B_{ww}B_{gw}\sigma_{wg,t-1} + 2B_{cw}B_{ew}\sigma_{ce,t-1} + 2B_{cw}B_{gw}\sigma_{cg,t-1} + 2B_{ew}B_{gw}\sigma_{eg,t-1}\end{aligned} \tag{3.5}$$

The variance equations for each market are presented in Appendix 3. Equation 3.5 suggests that wheat variance may be affected through several channels. First, wheat variance may be affected by its own lagged mean equation errors, A_{ww}^2, and lagged variance, B_{ww}^2. Second, variance may also be affected by lagged mean equation errors in the other three markets: corn (A_{cw}^2), ethanol (A_{ew}^2), or gasoline $\left(A_{gw}^2\right)$[16]. Third, wheat variance may be affected by the lagged variance in each of the other three markets: corn (B_{cw}^2), ethanol (B_{ew}^2), or gasoline $\left(B_{gw}^2\right)$. Fourth, the wheat variance may also be affected by the lagged covariances of between all markets: wheat and corn ($2B_{ww}B_{cw}$), wheat and ethanol ($2B_{ww}B_{ew}$), wheat and gasoline $\left(2B_{ww}B_{gw}\right)$, corn and ethanol ($2B_{cw}B_{ew}$), corn and gasoline $\left(2B_{cw}B_{gw}\right)$, and ethanol and gasoline $\left(2B_{ew}B_{gw}\right)$.

[16] The other three terms associated with ARCH coefficients, $2A_{11}A_{2,1}$, $2A_{11}A_{3,1}$, and $2A_{11}A_{4,1}$ are generally difficult to interpret and have little economic meaning.

3.3 Data and Preliminary Tests

The weekly data for each market is from July 4^{th}, 2008 to April 27^{th}, 2018 and is described in Chapter 2, Section 2.3. The summary statistics of each price series is presented in Table (2-1), and each data series is plotted in Figure (2-1). The Augmented Dicky-Fuller (ADF) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test results in Table (2-2) suggest that each market price series is non-stationary. First-differencing each of the logged price series results in price changes that are stationary. The summary statistics of each price change series is presented in Table (2-3), and each price change series is plotted in Figure (2-2).

The Johansen cointegration test results in Table (2-4) identify that there is one significant cointegrating relationship between all markets, and the cointegrating relationship is presented in Equation 2.8. A preliminary VECM is estimated and the results are presented in Table (2-5) and discussed in Section 2.4. An important assumption about the validity of the VECM is that the errors follow a homoscedastic process. An ARCH-LM test is performed on the VECM residuals and results indicate that autocorrelation is statistically significant[17]. The results of the ARCH-LM test validate the decision to model the VECM with a BEKK-MGACRH process.

3.4 Structural Breaks and the BEKK-MGARCH Model

Not accounting for parameter changes in the model may confound the GARCH results and produce spurious volatility relationships (Hildebrand 2005; Dijk et al. 2005). Therefore, a Nyblom (1989) stability test is used to test for structural breaks in the VECM-BEKK-GARCH model parameters. The null hypothesis in the Nyblom stability test is that a series of estimated model parameters, θ, follow a martingale process. A martingale process is a sequence of random variables

[17] The value of the test statistic was larger than the 1% critical value. Therefore, the null hypothesis that the residuals series are not serially correlated is rejected.

whose conditional expectation of the next value of the sequence, given all past values, is equal to the present value. The null and alternative hypotheses of the Nyblom stability test is:

$$H_0: \theta_{t+1} = \theta_t + v_t,\ \ var(v) = 0$$
$$H_1:\ \theta_{n+1} = \theta_t + v_t,\ \ var(v) > 0 \tag{3.7}$$

Specifically, the series of estimated parameters in Equation 3.7 follow a martingale process when the variance of a random variable, v_t, is equal to zero. The alternative hypothesis is that the series of estimated model parameters do not follow a martingale process, and therefore the parameters are unstable.

The Nyblom stability test is applied to a preliminary VECM-BEKK-GARCH model and the results are presented in Table (3-1). The Nyblom stability test reveals that there are ten breaks within the VECM-BEKK-GARCH model. In general, the breaks tend to take place within the two periods that are discussed in previous sections; the 2008-2010 financial crisis period and 2013-2014 when crop prices were volatile.

Table 3-1: Nyblom Stability Test Results

Parameter	Test Statistic	P-Value	Estimated Break Date
C_{cc}	0.750	0.01	September 30, 2011
C_{gc}	0.368	0.09	December 4, 2014
C_{ge}	0.436	0.06	September 19, 2014
C_{gg}	0.435	0.06	September 19, 2014
A_{wc}	0.806	0.01	January 9, 2009
A_{we}	0.942	0.00	January 9, 2009
B_{we}	0.543	0.03	March 8, 2013
B_{cc}	0.567	0.03	October 8, 2010
B_{cg}	0.473	0.05	November 28, 2014
B_{gg}	0.357	0.09	September 19, 2014

To control for these break dates, time dummies are included in the BEKK volatility model. The time dummies are incorporated into the model in a way that ensures the variance-covariance matrix remains positive definite and ensures that the estimated parameters on the time dummies can be positive or negative. The BEKK model augmented with the time dummies is expressed as:

$$H_t = (C + E_1 d_{1,t} + E_2 d_{2,t})'(C + E_1 d_{1,t} + E_2 d_{2,t}) + A u_{t-1} u'_{t-1} A + B' H_{t-1} B \tag{3.8}$$

The first time dummy covers the period from July 4th, 2008 to October 8th, 2010. The second time dummy covers the period March 8th, 2013 to December 4th, 2014. The $E_{1,t}$ and $E_{2,t}$ variables are $K \times K$ lower triangular matrices of the estimated time dummy parameters in period, t, respectively. The $d_{1,t}$ and $d_{2,t}$ variables are $K \times 1$ matrices of the 2008-2010 and 2013-2014 time dummies in period, t, respectively. By introducing the time dummies in the BEKK model, the intercept component of the variance equations become more complex. The variance equations for each market with the new intercept and dummy components are presented in Appendix 4. As an example, the augmented variance equation for wheat is presented in Equation 3.9:

$$\begin{aligned}
\sigma_{1,t}^2 = {} & \left[\boldsymbol{C_{ww}} + \boldsymbol{E_{ww,1} d_{1,t}} + \boldsymbol{E_{ww,2} d_{2,t}}\right]^2 + A_{ww}^2 u_{w,t-1}^2 + A_{cw}^2 u_{c,t-1}^2 + A_{ew}^2 u_{e,t-1}^2 + A_{gw}^2 u_{g,t-1}^2 \\
& + 2A_{1w} A_{cw} u_{w,t-1} u_{c,t-1} + 2A_{ww} A_{ew} u_{w,t-1} u_{e,t-1} + 2A_{cw} A_{ew} u_{c,t-1} u_{e,t-1} \\
& + 2A_{ww} A_{gw} u_{w,t-1} u_{g,t-1} + 2A_{cw} A_{gw} u_{c,t-1} u_{g,t-1} + 2A_{ew} A_{gw} u_{e,t-1} u_{g,t-1} + B_{ww}^2 \sigma_{w,t-1}^2 \\
& + B_{cw}^2 \sigma_{c,t-1}^2 + B_{ew}^2 \sigma_{e,t-1}^2 + B_{gw}^2 \sigma_{g,t-1}^2 + 2B_{ww} B_{cw} \sigma_{wc,t-1} + 2B_{ww} B_{ew} \sigma_{we,t-1} \\
& + 2B_{ww} B_{gw} \sigma_{wg,t-1} + 2B_{cw} B_{ew} \sigma_{ce,t-1} + 2B_{cw} B_{gw} \sigma_{cg,t-1} + 2B_{ew} B_{gw} \sigma_{eg,t-1}
\end{aligned} \tag{3.9}$$

3.5 Model Results with Period Dummy Variables

3.5.1 Mean Equation Results

The full VECM-BEKK-GARCH system with time dummies is estimated[18], and the mean equation results are presented in Table (3-2).

Table 3-2: VECM with BEKK specification

Wheat Equation		Corn Equation		Ethanol Equation		Gas Equation	
Variables	Coeff.	Variables	Coeff.	Variables	Coeff.	Variables	Coeff.
Constant	0.11***	Constant	0.007	Constant	0.214***	Constant	-0.005
Wheat (-1)	0.146***	Wheat (-1)	0.075	Wheat (-1)	0.033	Wheat (-1)	0.110**
Corn (-1)	0.06**	Corn (-1)	-0.045	Corn (-1)	0.137***	Corn (-1)	0.120***
Ethanol (-1)	0.011	Ethanol (-1)	0.034	Ethanol (-1)	0.021	Ethanol (-1)	-0.004
Gas (-1)	-0.043	Gas (-1)	-0.053	Gas (-1)	0.040	Gas (-1)	0.194***
ECP	-0.026***	ECP	-0.002	ECP	-0.053***	ECP	0.001

Note: (-1) indicates that the variable has been lagged by one period.

ECP is the estimated error correction parameter of the error correction model.

There are significant cross effects from the corn market to the other three markets. Specifically, a one-percent increase (decrease) in corn prices today increases (decreases) ethanol and gasoline prices next week by about 0.14%, and 0.12%, respectively. A one-percent increase (decrease) to corn prices today increases (decreases) wheat prices next week by about 0.08%. Though the effect from corn to wheat is statistically significant, it is likely economically insignificant; a $0.05/bushel change to the price of corn translates to a $0.15/tonne change to the price of wheat. The only other significant cross effect is from the wheat market to the gasoline market. A one-percent increase (decrease) in wheat prices today increases (decreases) gasoline prices next week by about 0.11%.

[18] An ARCH-LM test is performed on the residuals, and the test fails to reject the null hypothesis that there is no serial correlation.

Corn price changes are not affected by price changes in any market. One explanation for this result is that corn can be easily reallocated from one use to another (i.e. from animal or human consumption to ethanol production), which means that the corn market can withstand demand shocks. Instead, exogenous factors like government policies and environmental conditions are associated with short-run changes to corn prices (Abbott et. al 2008).

Only wheat and ethanol prices adjust to a deviation in the long run equilibrium relationship with the corn and gasoline prices. Specifically, wheat and ethanol prices adjust to their equilibrium values at a rate of 2.6% and 5.3% per week, respectively. These results suggest that it takes wheat prices approximately 38 weeks, and ethanol prices approximately 19 weeks, to adjust to their equilibrium price levels. The insignificant ECP in the corn and gasoline markets indicate that following a shock to the equilibrium relationship with wheat and ethanol prices, corn and gasoline prices do not adjust back to their equilibrium price levels. This result suggests that the corn and gasoline markets are exogenous to the cointegrating system.

3.5.2 Variance Equation Results

A Nyblom stability test is conducted on the model, and the results are presented in Table (3-3). The results of the Nyblom stability test suggest that the incorporation of the time dummies in the BEKK component has eliminated the instability of the GARCH parameters.

Table 3-3: Nyblom Stability Test Results with Time Dummies

Parameter	Test Statistic	P-Value	Estimated Break Date
C_{cc}	0.045	0.90	-
C_{gc}	0.034	0.96	-
C_{ge}	0.109	0.52	-
C_{gg}	0.142	0.40	-
A_{wc}	0.081	0.67	-
A_{we}	0.256	0.18	-
B_{we}	0.069	0.75	-
B_{cc}	0.088	0.63	-
B_{cg}	0.025	0.99	-
B_{gg}	0.195	0.27	-

The variance equation parameters are presented in Table (3-4). Wheat market volatility is not affected by price shocks in the corn, ethanol, or gasoline markets. Only price shocks to wheat affect wheat market volatility. About 8.4% of a positive (negative) price shock to wheat this week increases (decreases) wheat market volatility next week. Wheat market volatility is not affected by lagged volatility in the corn, ethanol, or gasoline markets market. Instead, wheat market volatility is highly persistent. About 91% of the market volatility that is observed in the wheat market this week is transmitted into next week. Wheat market volatility is not sensitive to changes in covariance between any two markets.

Corn market variance is not affected by price shocks in the wheat, ethanol, or gasoline markets. Only price shocks to corn affect corn market volatility. About 6.9% of a positive (negative) price shock to corn this week increases (decreases) corn market volatility next week. Corn market volatility is not affected by price volatility in the wheat, ethanol, or gasoline markets, nor is it persistent. However, price change volatility in the corn market is sensitive to the covariance between wheat and corn. About 22% of a positive (negative) change to wheat and corn covariance this week increases (decreases) corn volatility next week.

Ethanol market variance is not affected by price shocks in any market. However, volatility in the ethanol market is affected by price volatility in the wheat market. About 6.8% of an increase (decrease) to wheat price volatility this week increases (decreases) ethanol price volatility next week. Ethanol price volatility is also quite persistent, where about 84% of the market volatility in the ethanol market this week is transmitted into next week. Volatility in the ethanol market is also sensitive to changes in the covariance between wheat and ethanol. About 48% of an increase (decrease) to wheat and ethanol covariance this week changes ethanol market volatility next week.

Gasoline market volatility is not affected by price shocks in the wheat, corn, or ethanol markets. Only price shocks to gasoline affect gasoline market volatility. About 8.8% of a positive (negative) price shock to gasoline this week increases (decreases) gasoline market volatility next week. Volatility in the gasoline market is not affected by volatility in the wheat, corn, or ethanol markets, but it is persistent. About 70% of the volatility in the gasoline market this week is transmitted to next week. Gasoline market volatility is also sensitive to the covariance between corn and gasoline. About 28% of a positive (negative) change to corn and gasoline covariance this week decreases (increases) gasoline market volatility next week.

Table 3-4: Variance Equation Parameters of BEKK with Time Dummies

Constant	Coeff.	**ARCH**	Coeff.	**GARCH**	Coeff.	**Covariance**	Coeff.
				Wheat			
C_{ww}^2	0.000	A_{ww}^2	0.084***	B_{ww}^2	0.910***	$2B_{ww}B_{cw}$	-0.216
$E_{ww,a}^2$	0.000	A_{cw}^2	0.004	B_{cw}^2	0.013	$2B_{ww}B_{ew}$	-0.057
$E_{ww,b}^2$	0.000	A_{ew}^2	0.004	B_{ew}^2	0.001	$2B_{ww}B_{gw}$	-0.015
		A_{gw}^2	0.001	B_{gw}^2	0.000	$2B_{cw}B_{ew}$	0.007
						$2B_{cw}B_{gw}$	0.002
						$2B_{ew}B_{gw}$	-0.000
				Corn			
C_{cc}^2	0.001***	A_{wc}^2	0.041	B_{wc}^2	0.088	$2B_{cc}B_{wc}$	0.221**
$E_{cc,a}^2$	0.000	A_{cc}^2	0.069*	B_{cc}^2	0.139	$2B_{cc}B_{ec}$	-0.002
$E_{cc,b}^2$	0.000	A_{ec}^2	0.002	B_{ec}^2	0.000	$2B_{cc}B_{gc}$	-0.032
		A_{gc}^2	0.051	B_{gc}^2	0.002	$2B_{wc}B_{ec}$	-0.002
						$2B_{wc}B_{gc}$	-0.005
						$2B_{ec}B_{gc}$	-0.000
				Ethanol			
C_{ee}^2	0.000	A_{we}^2	0.000	B_{we}^2	0.068**	$2B_{ee}B_{we}$	0.476***
$E_{ee,a}^2$	0.000	A_{ce}^2	0.001	B_{ce}^2	0.012	$2B_{ee}B_{ce}$	-0.197
$E_{ee,b}^2$	0.000	A_{ee}^2	0.017	B_{ee}^2	0.835***	$2B_{ee}B_{ge}$	-0.029
		A_{ge}^2	0.000	B_{ge}^2	0.000	$2B_{we}B_{ce}$	-0.056
						$2B_{we}B_{ge}$	-0.008
						$2B_{ce}B_{ge}$	0.003
				Gasoline			
C_{gg}^2	0.000	A_{wg}^2	0.005	B_{wg}^2	0.004	$2B_{gg}B_{wg}$	0.102
$E_{gg,a}^2$	0.000	A_{cg}^2	0.010	B_{cg}^2	0.028	$2B_{gg}B_{cg}$	-0.278*
$E_{gg,b}^2$	0.000	A_{eg}^2	0.006	B_{eg}^2	0.000	$2B_{gg}B_{eg}$	0.009
		A_{gg}^2	0.088**	B_{gg}^2	0.695***	$2B_{wg}B_{cg}$	-0.020
						$2B_{wg}B_{eg}$	0.001
						$2B_{cg}B_{eg}$	-0.002

* Significant at the 10% level.
** Significant at the 5% level.
***Significant at the 1% level.

3.6 Conclusions

Investment in second-generation ethanol production facilities depends on future input and output price variability (Markel et al. 2018; McCarty and Sesmero 2015). Even though time series price data for second-generation feedstock prices (i.e. wheat straw prices) is unavailable, wheat grain prices are likely correlated to the supply of wheat straw since straw is a by-product of wheat. Therefore, this analysis has investigated important price and price volatility relationships between Canadian wheat and US corn, ethanol, and gasoline markets, in order to gain insights into future price scenarios that may influence whether a second-generation ethanol industry could emerge in Western Canada. There are several important takeaways from this analysis.

3.6.1 Results from the VECM Analysis

As a precursor to the VECM analysis, a Johansen cointegration test was used to identify if an equilibrium relationship exists between the four markets under consideration. A long run relationship between all markets is identified.

Short-run price changes in the ethanol market are dictated by shocks to the long run price relationship. This result could have financial implications for first and second-generation producers. First generation ethanol producers may experience lower profits (if ethanol prices decrease relative to corn prices) or higher profits (if ethanol prices increase relative to corn prices) in the short-run. This result may be explained by a long-run zero-profit relationship between corn and ethanol. If the price of corn and ethanol are such that first-generation ethanol producers make positive (negative) profits, ethanol production expands (contracts) and ethanol prices decrease (increase) so that profits are zero in the long-run (Mallory, Irwin and Hayes; 2012). Similarly, the financial position of second-generation ethanol producers could benefit from higher ethanol prices or suffer from lower ethanol prices in the short-run.

Short-run price changes in the wheat market are dictated by shocks to the equilibrium price relationship, which may have financial implications for a second-generation ethanol industry. A positive (negative) shock to the equilibrium system that causes wheat prices to adjust to a higher (lower) equilibrium price may encourage farmers to grow wheat more (less) frequently. In turn, there may be more (less) wheat straw available for ethanol production. However, in the long run wheat prices could return to the equilibrium level with the other prices.

Because short-run price dynamics may affect the variability of output prices and feedstock supply, investors and policy makers could consider strategies that counteract unfavourable price changes to wheat and ethanol caused by changes to their relationship with the corn and gasoline markets.

3.6.2 Results from the BEKK-GARCH Analysis

A first important result of the volatility analysis is that price change volatility is persistent in the wheat, ethanol, and gasoline markets. A second important result is that there are no significant price change shock effects from one market to another. These two results are good news for first and second-generation producers; market volatility in the feedstock and output markets is not vulnerable to price shocks to any market. The lack of significant price change shock transmission effects may reflect current risk management strategies in the first-generation ethanol industry. For example, ethanol producers use hedging strategies like trading the corn-crush spread, which is the difference between the revenue value of ethanol and distillers' dried grains (DDG) and the cost of corn, to minimize their exposure to unfavourable price movements in the corn market (CME Group, 2010).

Overall, the results from this analysis yield important information pertaining to the price and price volatility transmission relationships among the four markets under consideration.

However, the structure of these relationships may change if a second-generation ethanol industry develops.

Chapter 4: A Wheat Straw Feedstock Supply Response Model for Cellulosic Ethanol Production in Western Canada

4.1 Introduction

Concerns regarding the use of cereal grains for fuel have triggered an interest in second-generation (i.e. cellulosic) ethanol. Wheat straw has been identified as a potential feedstock for second-generation ethanol production in multiple jurisdictions (Talebnia et al. 2010; Saha et al. 2005). If a second-generation ethanol industry is to emerge in Canada, ethanol processing facilities require a consistent and reliable supply of biomass feedstock.

Although wheat is widely grown in Western Canada, the availability of wheat straw for ethanol production is uncertain. The supply of wheat straw can vary spatially and temporally in response to many factors. Specifically, the price and yield expectations of wheat relative to other crops could determine whether a farmer grows wheat or another crop. If wheat is grown, wheat grain and straw yields can vary depending on environmental conditions and farm management decisions. Whether farmers agree to sell their straw depends on the prices that biorefineries are willing to offer, relative to benefits the farmer gets by retaining wheat straw on the field or what they might receive from growing other crops.

Wheat straw is a natural resource that has many uses. Wheat straw can be used to help cultivate fruits and vegetables, create value added products like pet litter, drinking straws, paper, and plastic, and create construction materials like building bricks and insulation (Yuan and Sun 2010; Kretschmer et al. 2012). Furthermore, the combustion and gasification of wheat straw has the potential to produce renewable heat and electricity (Giuntoli et al. 2013; Kaparaju et al. 2010). In Canada, wheat straw has been traditionally used in the livestock sector. From 1996 to 2004, approximately twenty-eight percent of the total straw produced each year in Alberta, Saskatchewan, and Manitoba was used for cattle bedding and feed (Sokhansanj et al. 2006).

Wheat straw may also be shredded and spread on to the soil surface. Returning wheat straw to the soil surface can regulate soil temperature and moisture, promote healthy soil bacteria and microorganisms, reduce topsoil erosion, and add organic nutrients to the soil (Kumar and Goh 1999). However, the extent to which organic nutrients are accumulated and depleted because of straw management decisions is not well established. A body of literature that has conducted long-term field experiments in Western Canada has found that wheat straw residues significantly affect organic nitrogen, carbon, and other organic elements in cultivated soils (Malhi et al. 2006; Campbell et al. 1999; Campbell et al. 1990; Carefoot et al. 1994). However, other studies performed in Western Canada have concluded that removing crop residues from the surface may not have an immediate effect on the level of organic nutrients in the soil or crop yields (Soon 1998; Zentner et al. 1987; Stumborg et al. 1996, Lafond et al. 2009). For example, long term studies in Saskatchewan have found that consistent straw removal may not have a noticeable affect on soil quality over time (Lafond et al. 2012). Despite the inconsistencies in the soil science literature, wheat straw is often cited as being an important contributor to organic nutrients in soil that benefit crop yields. For this reason, the price of wheat straw is often associated with the price of fertilizer (Franzen 2017; Lindsey and Lentz 2019; Evans 2019; Langlois 2019).

A significant body of literature has investigated the potential supply of agricultural residues for biofuel production. In general, the methods adopted in the literature can be categorized into two groups: the inventory method and the economic method (Gronowska et al. 2009).

The inventory method makes assumptions about economic dimensions that affect residue supply. Certain quantities of residues are assumed sold to alternative markets or retained for soil amendments, and then deducted from the total available residue stock (Gronowska et al. 2009). The inventory method has been used in papers that conduct financial analyses of second-generation ethanol production facilities (Mupondwa et al. 2018; Zhang et al. 2017; Maung et al. 2013; Leistritz et al. 2006; Mabee and Saddler 2010; Mabee et al. 2004). For example, Mupondwa et al. (2017) investigate economic and technoeconomic factors to assess the profitability of a cellulosic ethanol plant in Saskatchewan. The authors use the inventory method to estimate residue availability for ethanol production by subtracting residues for livestock and soil conservation. Likewise, regional studies in Canada have used the inventory method to estimate feedstock supply as part of a larger effort to gauge the feasibility of fuel and energy production from agricultural residues (Oo and Lalonde 2012; Prairie Practitioners Group Ltd. 2008; Helwig et al. 2002). Other papers have used the inventory method to investigate the availability of agricultural residues for biofuel production (Wood and Layzell 2003; Mabee et al. 2006). For example, Li et al. (2012) use the inventory method to estimate the total availablity of crop residues for ethanol production in Canada. The authors conclude that of the 82.35 million tonnes of crop residues produced on average annually in Canada from 2001-2010, 47.9 million tonnes could have been available for ethanol production and the remaining crop residues could have been used for soil conservation and livestock purposes.

The economic approach models the supply of residues under different economic conditions. The relationships between residue supply and residue prices and costs associated with harvesting and transporting residues are investigated (Gallagher et al. 2003; Archer and Johnson 2012; Haq and Easterly 2006). For example, Yemshanov et al. (2018) use the economic approach to estimate aggregate residue supply curves in Canada using data from 2006-2014. The authors conclude that a large supply of agricultural residues, approximately 57 million tonnes, may be available at low residue prices due to low collection costs. The economic method has also been used to investigate how the residue supply response of farmers may vary under different price and yield environments. These papers focus on corn stover for ethanol production in the US. Specifically, models have been used to explore the profit-maximizing strategy of farmers who have the option to select different crop rotations and corn stover management decisions (Sesmero and Gramig 2013; Sesmero et al. 2015). For example, Thompson and Tyner (2014) use a time-invariant linear programming model to show that farmers may allocate more land to continous corn rotations when the price of corn stover is high. Similarily, Kurkalova and Tran (2018) simulate net returns from grain and stover harvests under different tillage systems and conclude that higher stover prices incentivize farmers in Iowa to continously grow corn.

This paper adopts an economic approach by explicitly modelling benefits and costs that influence economic choices of farmers regarding wheat straw supply. In pursuing this approach, there are several important differences between the economic analyses in the current literature and the analysis conducted in this paper.

A major difference is that this analysis investigates environmental and economic variables that may affect wheat straw availability. In the existing literature, the amount of crop residues that are available for ethanol production are adjusted in various ad hoc ways to account for some residues that are assumed to be retained by the farmer to maintain soil quality. However, these models do not explore specific conditions that could vary the amounts supplied. In this analysis, soil quality is a state variable that can be influenced by farmers' crop choices, and whether to leave or collect and sell wheat straw. Furthermore, the existing literature treats environmental and economic factors that could affect the availability of residues as static. However, these variables could likely change over time. In this paper, mean crop yields are deterministically related to soil quality and farm management decisions but yields also vary stochastically around the mean due to weather conditions and crop diseases. Likewise, in this paper, crop and straw prices follow stochastic mean-reverting processes. Under these price processes, profit expectations for available crop and soil management options change from year to year, which means that optimal choices may also change over time.

Another important distinction between this analysis and the current literature is regarding geographical location and resolution. This analysis uses county, regional, and provincial data to investigate the straw management decisions of a farmer in Alberta, Canada. It is important to perform an economic analysis at the farm level because empirics suggest that there is a significant degree of spatial heterogeneity to crop and residue prices and to environmental factors that affect crop yields. Therefore, the availability of straw for ethanol may vary from farmer-to-farmer. Given appropriate parameters, this model can be used to investigate the straw management decisions of farmers across the province of Alberta.

Finally, this paper adds to the existing literature by considering how the availability of crop residues may change in the future due to structural changes in crop residue markets caused by new demands for residues from cellulosic ethanol producers. Current wheat straw prices reflect the demand for straw from animal bedding and feed markets and the value of wheat straw as a soil organic matter (SOM) additive. This paper investigates how structural shifts to the distribution of wheat straw prices, due to an increase in straw demand from a second-generation ethanol producer, may affect the crop choice and straw management decisions of a farmer.

Overall, the results from this analysis could inform prospective ethanol producers about how ethanol feedstock supply may vary over time, given that farmers decisions are influenced by varying agricultural price and yield environments. With this information, prospective ethanol producers could be in a better position to assess spatial feedstock availability for large scale investments. Moreover, if investment is warranted, the information supplied by this model could be used to inform the design of purchasing agreements to secure a consistent and reliable supply of straw from local farmers.

In the next section, the economic model is developed and calibrated. Section 4.3 presents and discusses the results of the model, while Section 4.4 provides a summary and conclusions of the results.

4.2 Methods

This section begins by specifying a mathematical model of a farmer's decision problem. The model contains parameters, both deterministic and stochastic, that affect the farmer's crop choices and straw management decisions.

4.2.1 Dynamic Programming Overview

Dynamic programming is a mathematical optimization method that considers how the current management of assets affects the future value of a given objective function (Bellman 1954). In this chapter, a dynamic programming model is used to capture crop and straw management decisions of a typical farmer. The asset under consideration is soil, which is modelled as two state variables: soil organic matter (SOM), and surface residues that have not been incorporated into the soil. The surface residues are included here as a transitory state variable because it is the source of SOM and because the process of incorporating it into the soil is not instantaneous, nor does all of it ultimately end up in the soil. The objective of the farmer is to maximize expected present value of all future agriculture profits. Farmers are assumed to maximize the objective by deciding which crops to plant (wheat or canola) and whether to collect and sell straw. Crop and straw management decisions are assumed to follow a sequence which is repeated annually.

Figure (4-1) displays the farmer choices in sequence. The crop choice, either wheat or canola, occurs in the spring. Crops are harvested in the fall when wheat and canola prices are realized. Therefore, crop prices and revenues are not known at the time of planting and the farmer must make the planting decision based on the expected distribution of future prices of wheat and canola. It is assumed that canola residues have no market value, and therefore all canola residues are transferred to the soil. For wheat, the farmer decides to collect and sell straw under the assumption that current straw prices are known. Since SOM affects crop yields, and since collecting straw reduces the crop residue on the soil surface that contribute to SOM, future yields of wheat and canola are, in turn, influenced by collecting.

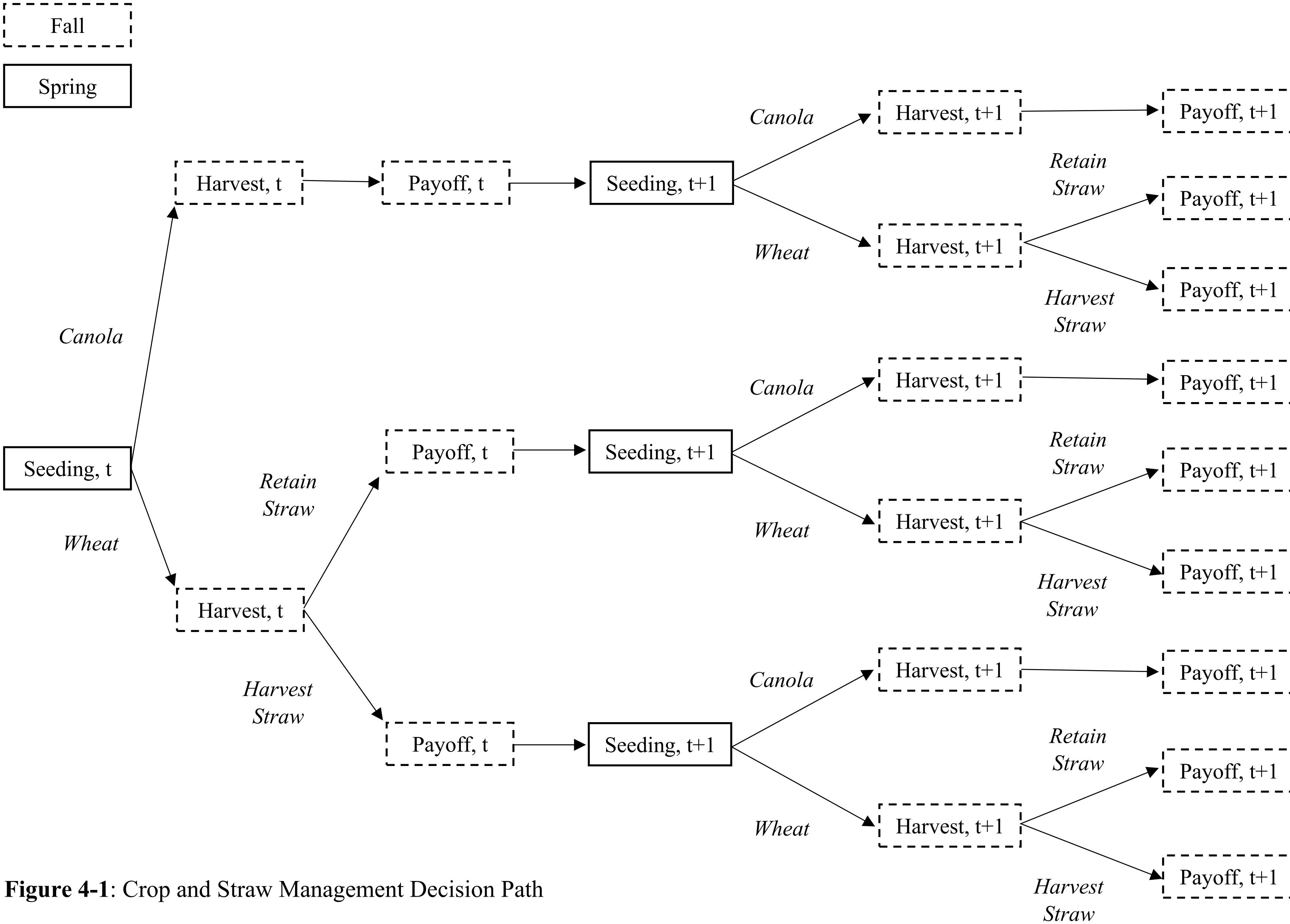

Figure 4-1: Crop and Straw Management Decision Path

4.2.2 Surface Residue and SOM States

There are several variables that can affect soil organic matter dynamics, such as climate, chemical properties of organic matter, decomposition rates of residues, and tillage practices (Stockmann et al. 2013). As a result, around 200 mathematical models have been developed to simulate organic matter dynamics (Campbell and Paustian 2015). For this paper, a parsimonious relationship between SOM dynamics and crop residues is used so that the analysis can focus on the complexities of decision making in response to varying prices, crop yields and disease, while still including the basics of soil dynamics.

Crop residues left behind on the soil surface from the crop harvest decompose slowly over time, and the release of organic nutrients is different depending on the crops and nutrients under consideration (Janzen and Kucey 1988; Lupwayi and Soon 2015; Soon and Arshad 2002; Lupwayi et al. 2004; Dormaar and Pittman 1980). Because only a fraction of the surface residues decomposes every year, surface residues can be thought of as a stock resource that grows and depletes depending on farm management practices. The stock of crop residues on the surface is affected by whether wheat or canola is grown; and if wheat is grown, whether the wheat straw is harvested. The dynamics of soil organic matter accumulation and depletion are complex. The essence of these complex processes are represented with:

$$\begin{aligned} R_{t+1} = R_{w,t} - R_{w,t}\left(\frac{\delta_{w,S} + \delta_{c,S}}{2}\right) + H_t\left[(1 - J_t)\alpha Y_{w,t}\right]\left(1 - \delta_{w,S}\right) \\ + (1 - H_t)\left[\mu Y_{c,t}\right]\left(1 - \delta_{c,S}\right) \end{aligned} \tag{4.1}$$

Equation 4.1 indicates that the amount of crop residue on the soil surface at a given time, R_{t+1}, is governed by several factors. The first is the stock of crop residues in the previous period,

R_t. This stock is constantly decomposing. This decomposition is represented as a constant annual rate by parameters $\delta_{w,S}$ (wheat) and $\delta_{c,S}$ (canola), which are a fixed numbers between 0 and 1. To simplify the model dynamics, it is assumed that wheat and/or canola surface residues decompose at the same average rate after one year. The term, $R_{w,t}\left(\frac{\delta_{w,S}+\delta_{c,S}}{2}\right)$ can be thought of as the natural loss of crop residues on the soil surface from period t to $t+1$. Second, additions to the surface residue stock are determined by the crop selection decisions. Specifically, H_t is a binary variable with a value equal to 1 or 0 if the farmer chooses to grow wheat or canola, respectively. The $Y_{w,t}$ and $Y_{c,t}$ variables are wheat and canola yields per hectare in period t, respectively. The wheat and canola yields are multiplied by α and μ parameters, which are the residue-to-grain (RTG) ratios for wheat and canola, respectively. Additions to the surface residue stock are also governed by the straw management choice of the farmer if wheat is grown. The straw management choice, J_t, is a binary variable with a value of 1 or 0 if straw is harvested and sold or kept for soil amendments, respectively. The model simplifies the dynamics by assuming that 100% of crop residues are removed when wheat straw is collected, which reduces the contribution to SOM for the year that it is removed.

The SOM dynamic equation is:

$$\begin{aligned} S_{t+1} = S_t - f(S_t) + H_t\left(Y_{w,t}\right)\left[\alpha\delta_{w,s}(1-J_t) + (1+\alpha)r_w\right] \\ + (1-H_t)\left(Y_{c,t}\right)\left[\mu\delta_{c,s} + (1+\mu)r_c\right] + R_t\left(\frac{\delta_{w,s}+\delta_{c,s}}{2}\right) \end{aligned} \tag{4.2}$$

where,

$$f(S_t) = 8.259{S_t}^{-0.976}$$

There are several important aspects to this formulation. First, the natural loss rate of SOM, $f(S_t)$, is a function of SOM. The function is calibrated by solving a system of first order conditions using historical yield and SOM data for different counties in Alberta, assuming Equations 4.1 and 4.2 are in a steady state (Olson 1963; Martel and Paul 1974). This calculation is presented in Appendix 5. Like the surface crop residue dynamics, the crop decision (H_t) and the straw management decision (J_t) affect the SOM stock dynamics. Growing wheat or canola produces different amounts of residues as per the RTG ratios (α, μ) which directly contribute to SOM. Crop root biomass is also a significant contributor to SOM (Kätterer et al. 2011; Dietzel et al. 2017). The crop root biomass of wheat and canola are calculated using r_w and r_c parameters, which are the root-to-biomass (RTB) ratios of wheat and canola, respectively. The root biomass of wheat and canola directly add to the stock of SOM, irrespective of the straw management choice for wheat. If wheat straw is harvested, only the decomposing endowment of crop residues on the soil surface, $R_t\left(\frac{\delta_{w,s}+\delta_{c,s}}{2}\right)$ and the portion from the roots, $Y_{w,t}(1+\alpha)r_w$, adds to the SOM stock.

4.2.3 Expected Crop Yields

Wheat and canola yields are modelled as a stochastic variable conditioned on soil organic matter. The expected value of wheat yields is:

$$E(Y_{is}^{w}) = \sum_i v_i Y_{is}^{w} \tag{4.3}$$

For wheat, Y_{is}^{w} is the yield of wheat conditional on random event, i and SOM level, *s,* and v_i is the probability of event, *i.* It is assumed that the random events (*i*=1, 2, or 3), which represent low, average, and high yields, depend primarily on weather and this distribution is independent of all other stochastic variables in the model.

Canola yields are also modelled as a stochastic variable conditioned on SOM. The expected value of canola yields is:

$$E\left(Y^{c}_{isd_t}\right) = \sum_{i,d_t} u_i \omega_{d_t} Y^{c}_{isd_t} \tag{4.4}$$

Canola yield, like wheat, is dependent on SOM and random event i. Canola yields are also dependent on the presence of canola disease. Therefore, for canola, $Y^{c}_{isd_t}$ is the yield conditional on random event *i,* SOM level *s*, and disease state *d* at time *t*. The parameter u_i is the probability of event *i*, which is primarily dependent on weather. The disease state is represented as binary, either present (d_t=1) or not present (d_t=0). However, unlike the weather event i, the probability of d_t is not independent of other variables in the model. The probability of canola disease in this year's crop, ω_{d_t}, is dependent on both the previous disease state (d_{t-1}) and on which crop was grown in the previous period (H_{t-1}). Hence, the probabilities ω_{d_t} can be written as a function of the previous states and decisions as follows: $\omega_{d_t} = \omega(d_{t-1}, H_{t-1})$.

The farmer has some control over the mean of future crop yields by managing crop residues, which affects SOM. The low, average, and high yield values and probabilities are calculated assuming the yields are normally distributed around the conditional mean yield which is a function of SOM. The conditional mean and standard deviation of the yields is estimated from a regression analysis of historical wheat and canola yields in Alberta. The wheat and canola yields are further discussed in Section 4.2.6.

4.2.4 Expected Profits

Expected profits for canola and wheat are functions of expected yields, prices, and other constant variables. Among the constant variables are the cost of harvesting wheat grain, h, and the cost of harvesting canola oilseed, m. Both costs are measured in CAD$/ha. The unit cost of harvesting wheat straw, g, is measured in CAD$/t and is also assumed constant over time.

The profits for wheat given a wheat price ($p_{w,t}$),wheat straw price ($p_{e,t}$), and yield $\left(Y_{is,t}^{w}\right)$ can be expressed as:

$$\Pi_{w,t} = p_{w,t} Y_{is,t}^{w} - h + (p_{e,t} - g)\alpha Y_{is,t}^{w} J_{p_{e,t}} \tag{4.5}$$

The straw price data used in this analysis does not reflect demand from ethanol producers. However, the price of straw in the future may reflect the demand from ethanol producer if an industry develops. Therefore, an important aspect of Equation 4.5 is that variable J_t is now $J_{p_{e,t}}$ to account for the possibility that straw collection decisions can vary depending on price for energy at time *t*. As before, $J_{p_{e,t}} = 1$ when straw is harvested, otherwise $J_{p_{e,t}} = 0$. The expected profit from growing wheat is:

$$E\left(\Pi_{w,t}\right) = E\left(Y_{is,t}^{w}\right)E(p_{w,t}) - h + E\left[(p_{e,t} - g)\alpha Y_{is,t}^{w} J_{p_{e,t}}\right] \tag{4.6}$$

The second expectation operates over both $p_{e,t}$ and $Y_{w,t}$. Probability distributions for wheat and straw prices are assumed to be conditional on previous prices: $p_{w,t-1}$ and $p_{e,t-1}$. Since the decision to harvest straw, $J_{p_{e,t}}$, is inside the expectation, the straw harvest decision can be made after the price $p_{e,t}$ is observed, allowing for straw harvest optimization contingent on the price of wheat straw. Since it is assumed that canola straw is not harvested, the expected value of canola only includes the expected value of the crop revenue:

$$E\left(\Pi_{c,t}\right) = E\left(Y_{isd_t}^{c}\right)E(p_{c,t}) - m \tag{4.7}$$

where, $p_{c,t}$ is the canola price, and m is the canola harvest cost. The canola price distribution is assumed to be conditional on the previous period's price, $p_{c,t-1}$. The expected prices are conditioned on previous prices, hence, so are the expected profits, $E(\Pi_{c,t})$. Section 4.2.7 investigates the time-varying processes of the price of wheat, wheat straw, and canola to formulate conditional price distributions that are used in the dynamic programming model. Overall expected profits for both crops, $E(\Pi_{w,t})$ and $E(\Pi_{c,t})$, are conditioned on four stochastic state variables ($p_{w,t}, p_{c,t}, p_{e,t}$ and d_{t-1}), two deterministic state variables (S_t and $R_{t,}$) and one previous decision (H_{t-1}) [19].

4.2.5 The Dynamic Programming Model

The farmer's decision problem is to choose the crop (H_t) and the straw management option ($J_{p_{e,t}}$) in each period that maximize the present value of farm profits. This decision problem can be expressed as a stochastic dynamic programming model where the recursive Bellman equation or value function is:

$$Z(R_{t,}S_t, H_{t-1}, d_{t-1}, p_t) = \max_{J_{p_{e,t}}, H_t} E\left[H_t \Pi_{w,t} + (1 - H_t)\Pi_{c,t} + \beta Z(R_{t+1,}S_{t+1}, d_t, H_t, p_{t+1})\right] \quad (4.8)$$

Subject to,

$$R_{t+1} = R_{w,t} - R_{w,t}\left(\frac{\delta_{w,S} + \delta_{c,L}}{2}\right) + H_t\left[(1 - J_t)\alpha Y_{is,t}^{w}\right](1 - \delta_{w,S}) + (1 - H_t)\left[\mu Y_{isd_t}^{c}\right](1 - \delta_{c,S})$$

$$S_{t+1} = S_t - f(S_t) + H_t(\alpha Y_{is,t}^{w})\left[\delta_{w,s}(1 - J_t) + r_w\right] + (1 - H_t)(\mu Y_{isd_t}^{c})\left[\delta_{c,s} + r_c\right] + R_t\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right)$$

$$R_0 > 0 \; is \; given$$

[19] The crop residue and SOM state variables depend on crop yields, which are stochastic due to random weather events. Therefore, while the processes for crop residue and SOM state variables are deterministic, the outcomes for these variables appear as stochastic.

$$S_0 > 0\ is\ given$$

The value function has 7 state variables: crop residues ($R_{t,}$), SOM (S_t), the presence or lack of canola disease at the end of the previous period (d_{t-1}), the crop decision from the previous period (H_{t-1}), and the price vector, $p_t = \left(p_{w,t}, p_{c,t}, p_{e,t}\right)$. The expectation operator, E, is applied over the stochastic variables (prices and disease states) for profits but also to the value function one period hence, where the future price and disease outcomes are conditioned on the current values of these variables.

The solution to the Bellman equation is found by maximizing the value function given an initial estimate of the value function in the future period (the third term inside the expectation on the right hand side of Equation 4.8). The right side of Equation 4.8 is maximized by selecting the best crop choice and straw management choice for all SOM, crop residue, canola disease, and agricultural price state combinations, of which there are 1,749,600. These maximized values constitute a new estimate of the value function, which is then used again as an estimate of the value function in the future period. The process is repeated iteratively until the value function converges, to a point where there is very small difference between the current and new estimates of the value function. This process was coded in R (version 3.5.3) and solved on a microcomputer with a 2.20 GHz quad-core processor with 32GB of RAM. The model took approximately 14 hours to solve. The details of the solution process for the Bellman equation are presented in Appendix 6.

4.2.5 Parameters and Constants

Table (4-1) contains the descriptions, values, and sources for the parameters that are used in Equations 4.1 to 4.8. The STG ratio for wheat is taken from a range of possible ratios across Alberta, and the STG ratio for canola is estimated from a set of observations in Clayton et al. (2000) and is consistent with other sources (Jackson 1999; Silvacom Ltd. and Green Analytics

2014). The wheat straw collection cost is a farmgate cost and includes the cost of baling and stacking large round straw bales and the nutrient value of wheat straw (Budynski 2020). Crop cost estimates for wheat and canola are available for different soil zones in Alberta, and the cost used in this analysis is the average cost between the black and grey soil zones (Manglai 2019). These two soil zones are the prevailing soil zones in the Edmonton-East geographical area defined by the Agriculture Financial Services Corporation (AFSC). The wheat and canola harvest costs include seeding, fertilizer, chemical applications, crop insurance, machinery, and labour costs. The discount factor, β, is chosen arbitarily to make the convergence of the dynamic optimation model faster.

Table 4-1: Values of Model Parameters

Parameter Description	*Parameter Value*	*Sources*
Decomposition rate of wheat straw (δ_w)	27%	Lupwayi et al. (2004)
Decomposition rate of canola residues (δ_c)	32%	Lupwayi et al. (2004)
Straw-to-grain ratio for wheat (α)	1.3	Sokhansanj et al. (2006)
Straw-to-grain ratio for canola (μ)	4.0	Clayton et al. (2000)
Root-to-biomass ratio for wheat (r_w)	0.23	Gan et al. (2009)
Root-to-biomass ratio for canola (r_c)	0.32	Gan et al. (2009)
Wheat straw collection cost (g)	$62.88/tonne ($CAD)	Budynski (2020)
Wheat harvest cost (h)	$272.89/ha ($CAD)	Manglai (2019)
Canola harvest cost (m)	$330.41/ha ($CAD)	Manglai (2019)
Discount factor (β)	0.90	-

4.2.6 Agricultural Yields

The relationship between agricultural yields and soil organic matter is well documented in soil science and agronomy literature. However, quantifying the relationship between organic matter and agricultural yield is often specific to the crop under consideration, the location where the study was undertaken, climactic factors during the study period, soil management practices, and fertilizer applications. Most of the international literature finds that higher organic matter concentration in soil is correlated with higher grain yields (Rasmussen and Parton 1994; Benbi and Chand 2007; Diaz-Zorita et al. 1999; Schjønning et al. 2018). For example, Ghaley et al. (2018) found that higher soil organic carbon (SOC) significantly increased winter wheat grain yields in Denmark at lower soil nitrogen levels. For higher nitrogen levels, the effects of SOC on yields plateaued. Recent global meta analyses use quadratic equations to model a concave relationship between SOM and yields, which suggests that there exists an optimal level of SOM to maximize agricultural production (Oldfield et al. 2020; Oldfield et al. 2019). Similar studies have been conducted in Western Canada to identify the relationship between SOM and wheat and canola yields. Monreal et al. (1997) model a positive and linear relationship between SOM concentration and wheat yields across select locations in Alberta and Saskatchewan. Similarly, Harker et al. (2011) and Harker et al. (2012) model a positive and linear relationship between SOM concentration and canola yields for select locations across Alberta, Saskatchewan, and Manitoba.

To model the relationship between SOM and agricultural yields in this analysis, the total average wheat and canola yields for 66 counties, measured in tonnes per hectare, are regressed on soil organic matter and geospatial coordinate data. Average agricultural yields from 2013-2017 are used in the regression analysis to reflect current trends in summer fallow and till practices in Alberta (Government of Canada 2020). Total average soil organic matter per county is calculated in several steps. First, ArcGIS is used to generate spatially weighted average SOM as a percent of total soil in each county. Total average soil at a 1 metre depth is then calculated for each county based on each county's representative soil zone (Alberta Agriculture, Food, and Rural Development n.d.). Total average SOM, which is measured in tonnes per hectare, is then calculated by multiplying total soil by the average SOM percentage for each county. The geospatial data that are used in both regressions are latitude coordinates for each county, which are measured in decimal degrees. A summary of the data used in these yield regressions is presented in Table (4-2).

Table 4-2: Summary Statistics of Yield Regression Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Canola (t/ha)	66	2.332	0.322	1.467	2.130	2.603	2.759
Wheat (t/ha)	66	3.997	0.652	2.381	3.656	4.402	5.493
Latitude (DD)	66	53.108	2.106	49.292	51.661	54.284	58.280
SOM (t/ha)	66	553.127	336.344	122.953	283.036	871.268	1,130.000

The historical data suggest that wheat yields have been more variable than canola yields, and that average wheat yields are nearly twice those of canola. There also tends to be significant variation in SOM across counties in Alberta. A transformed SOM variable is included in the wheat and canola yield functions to allow for the possibility of a non-linear relationship between SOM and crop yields. The transformation coefficient on the SOM variable is estimated by using a Box-Cox regression method. The transformation coefficient is estimated to be 0 for the wheat function and 0 for the canola function. Therefore, a log-transformed SOM variable is included in the wheat and canola yield functions. Constrained least squares is used to ensure that the estimated parameters for the log and linear SOM variables give a maximum yield at least as great as the maximum observed SOM in the county data. This ensures that yields are increasing throughout the SOM data range. Whether this relationship is increasing throughout the range is a question that could have implications for the farm management decisions that are modelled. This relationship could be the focus of further modelling to investigate the sensitivity of a farmer's decisions to the underlying relationship between SOM and crop yields. However, the analysis proceeds with the relationships prescribed. The results of the regressions are presented in Table (4-3). The implied equations for the wheat and canola yield functions based on the regression results are:

$$Y_k^w = 8.763 - 0.199L_k - 0.001S_k + 1.025ln(S_k) \tag{4.9}$$

$$Y_k^c = 6.547 - 0.122L_k - 0.0003S_k + 0.4ln(S_k) \tag{4.10}$$

where k is an index for counties ($k = 1, \dots, 66$); $Y_{w,k}$ and $Y_{c,k}$ are average crop yields over 2013-17 for wheat and canola in county *k;* S_k is the soil organic matter variable for county *k* and; L_k is the lattitude of the centroid of county *k.*

Table 4-3: Yield Regression Results

	Dependent Variable:	
	Wheat	Canola
	(1)	(2)
Latitude	−0.199****	−0.122****
	(0.051)	(0.024)
SOM	−0.001	−0.0003
	(0.001)	(0.0004)
ln(SOM)	1.025**	0.400*
	(0.459)	(0.218)
Constant	8.763****	6.547****
	(2.484)	(1.178)
Observations	66	66
R^2	0.239	0.296
Adjusted R^2	-	-
Residual Std. Error (df = 62)	0.583	0.277
F Statistic (df = 3; 62)	-	-
Note:	*p<0.1; **p<0.05; ***p<0.01; ****p<0.001	

Figure (4-2) show plots of the historical average wheat and canola yields plotted against SOM in each county, and the estimated yield functions for canola and wheat. The inclusion of log and linear SOM variables provides a better fit to the data than a quadratic equation. The parameters on the linear and log terms give an increasing and concave relationship between wheat and canola yields over the range of the data. Furthermore, wheat yields appear to be more sensitive to SOM than canola yields for all values of SOM. The negative latitude parameters in each yield function suggests that both wheat and canola yields are lower the further north a county is located. Specifically, wheat yields tend to be more sensitive to latitude than canola yields. The canola yield function is flatter than the wheat function, indicating that wheat responds more to increases in SOM than does canola.

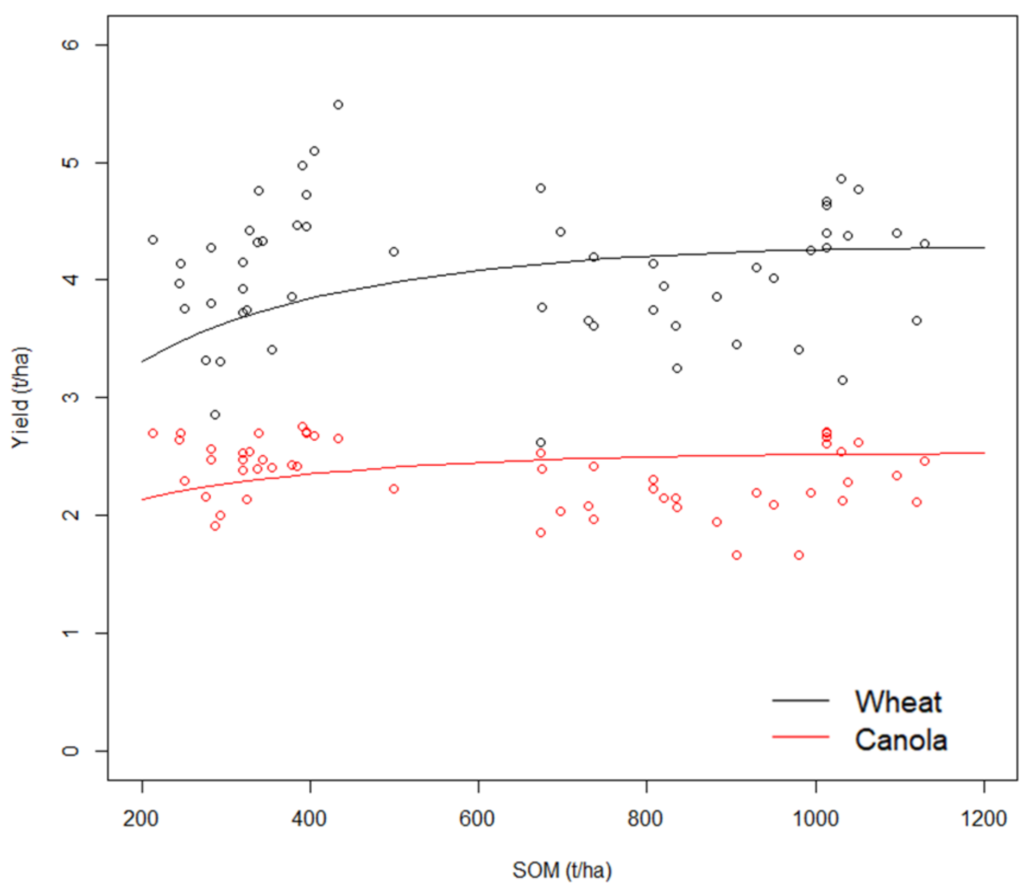

Figure 4-2: Scatter Plot of Wheat and Canola Yields vs SOM and the Yield Curves

4.2.7 Prices

The crop and wheat straw prices in Equations 4.5 to 4.8 are assumed to be conditional on past prices. To calibrate these conditional price relationships, historical price data that are available for wheat, canola, and straw across different sub-regions in Alberta are used. The straw prices are quarterly from 2008 to 2019, measured in CAD$/t, and are from the AFSC (Agriculture Financial Services Corporation 2020). The prices are available for five different zones in Alberta: Peace zone, Edmonton-North zone, Edmonton-East zone, Edmonton-Calgary zone, and Calgary-South zone. The straw prices that are used for the dynamic optimization analysis are from the Edmonton-East Region. The wheat and canola prices are daily spot prices[20] from September 2015 to September 2019, measured in CAD$/t, and are from the Alberta Wheat Commission, Price & Data Quotes (PDQ) (Alberta Wheat Commission n.d.). The Alberta Wheat Commission divides Alberta into four regions: Peace, Northern Alberta, Southern Alberta, and Northwestern Saskatchewan. The wheat and canola prices that are used for the dynamic optimization analysis are from the Alberta North region. Summary statistics of the price series are presented in Table (4-4).

Table 4-4: Summary Statistics of Agricultural Prices

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Straw (CAD/t)	47	48.642	14.920	30.865	37.479	57.320	92.594
Wheat (CAD/t)	1,024	247.376	17.628	202.840	238.355	258.275	340.200
Canola (CAD/t)	1,024	465.851	28.413	404.690	444.985	486.207	528.870

A plot of the straw prices by AFSC zone is presented in Figure (4-3), and plots of the wheat and canola prices from the Alberta North region are presented in Figure (4-4). Historically, the unit price of canola has been greater than the unit price of wheat in the Northern Alberta zone. The

[20] A Kalman filter is used to fill missing data points for the wheat and canola prices.

unit price of straw in the Edmonton-East zone has been significantly lower than the unit price of wheat grain. Straw prices have been the most variable because the coefficient of variation is the highest for wheat straw (0.31) compared to wheat (0.07) and canola (0.06).

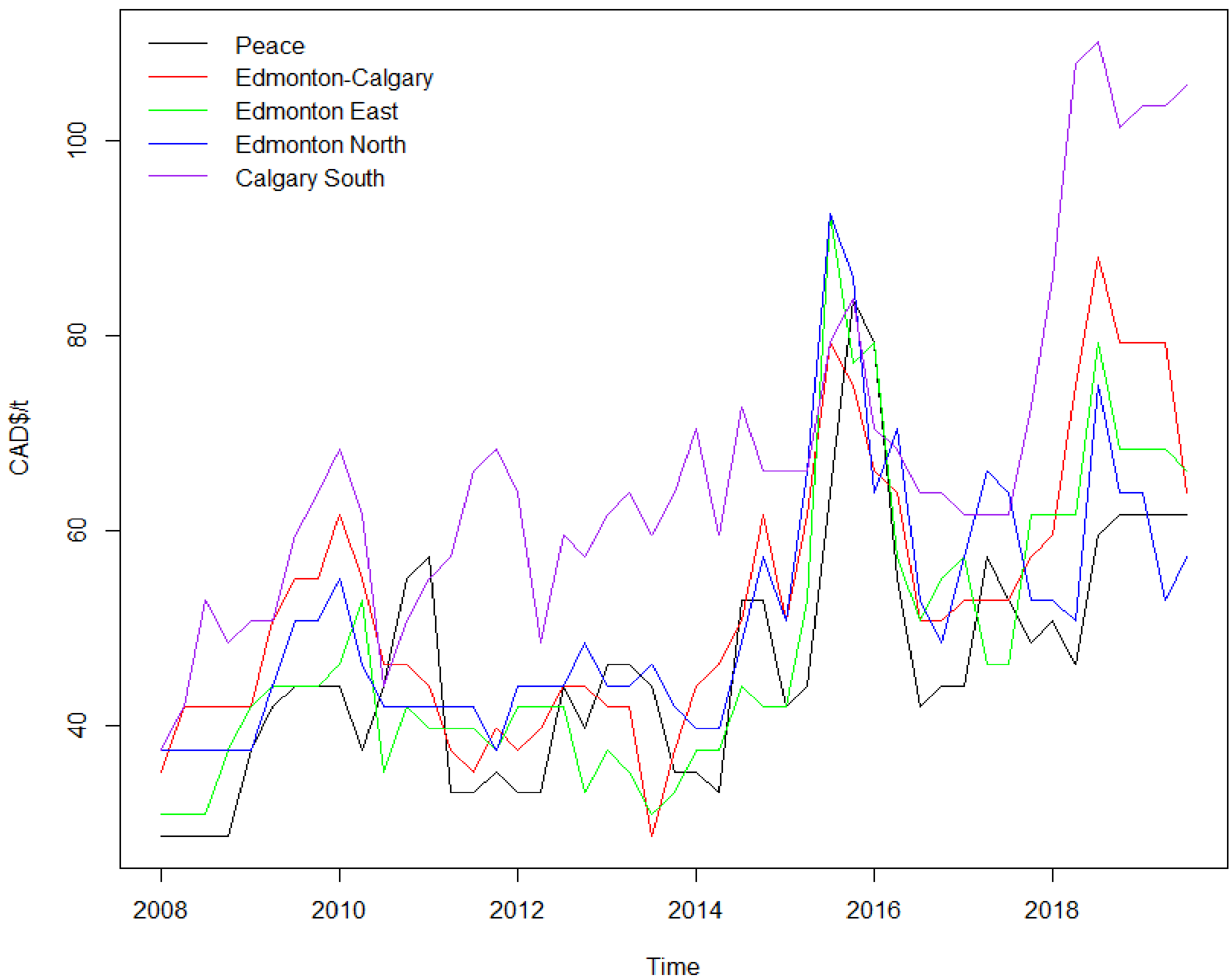

Figure 4-3: Historical Straw Prices by AFSC Zone

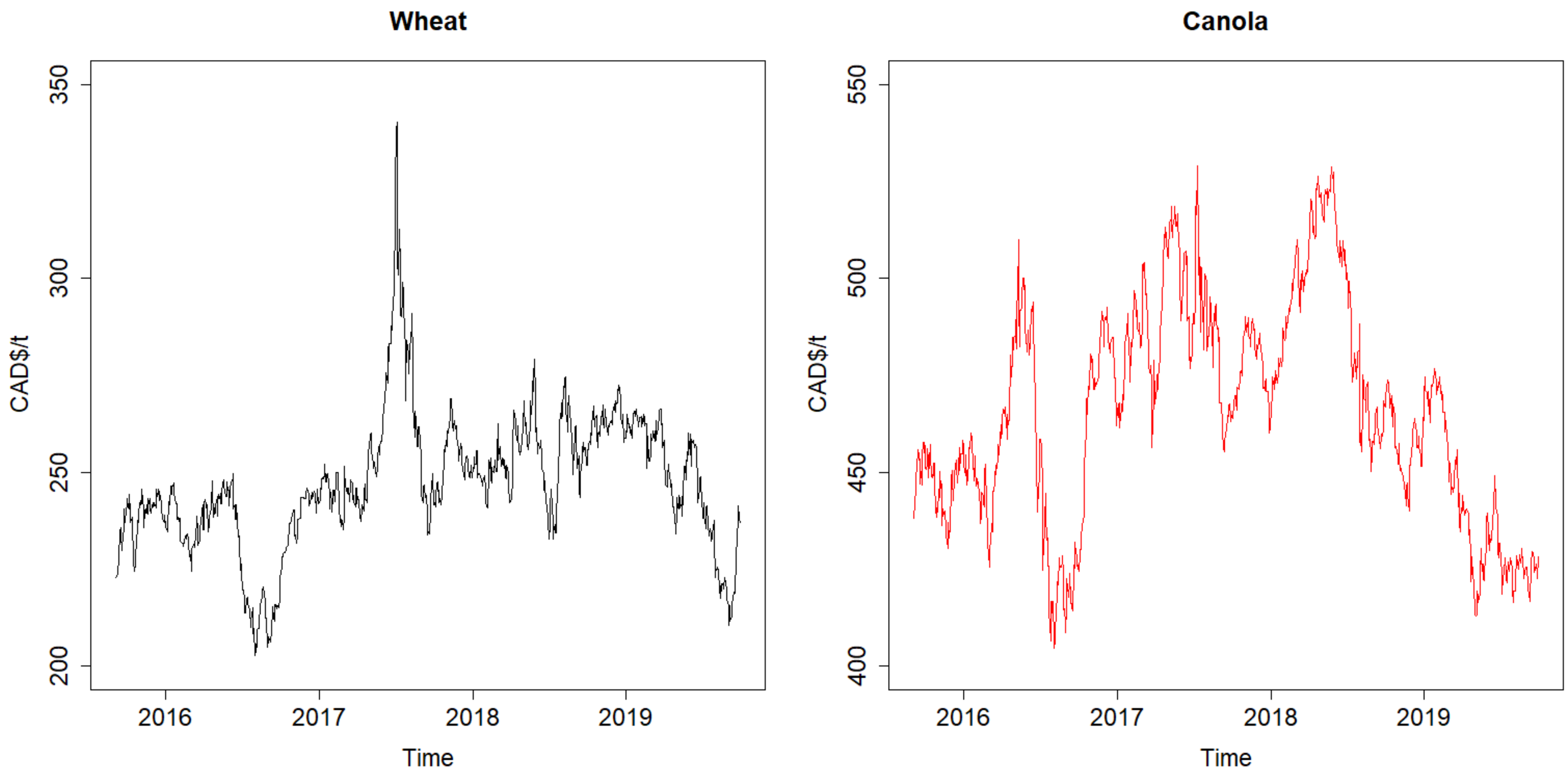

Figure 4-4: Historical Wheat and Canola Prices, Northern Alberta PDQ Zone

A visual inspection of the data in Figure (4-3) suggests that straw prices in each region are not stationary, as there appears to be an upward trend in each price over time. Furthermore, a visual inspection of the data in Figure (4-4) suggests that wheat prices may be stationary over time, and that canola prices may not be stationary. Preliminary tests are conducted on the wheat, canola, and straw prices to assess whether the prices are stationary. Augmented Dicky-Fuller (ADF) unit root tests were employed to test for stationary with no trend or drift, drift, and trend and drift. The number of lags included in each ADF test were selected using Bayesian Information Criterion (BIC). A KPSS test was also used to test the null hypothesis that each series was trend stationary. The results of the unit root tests are presented in Table (4-5).

Table 4-5: ADF and KPSS Test Results

	Wheat	**Canola**	**Straw**
ADF Tests			
None	-0.0337	-0.2266	0.0958
Drift	-3.5178***	-2.5354	-1.9683
Trend & Drift	-3.5061**[21]	-2.7306	-2.8155
KPSS Test	1.4086***	2.0591***	0.098927

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

The results of the tests reveal that the canola and straw prices are non-stationary, and the wheat prices are stationary with a drift term. However, for both practical and theoretical reasons, the analysis proceeds under the assumption that all series are stationary. On the practical side, the dynamic programming model requires that the price states follow a stationary process. In addition,

[21] The estimated time trend parameter is statistically insignificant.

the solution process for the Bellman equation requires a grid which automatically bounds the state variables. On the theoretical side, there is evidence to suggest that commodity prices are likely to be stationary over time after accounting for structural shifts in prices (Zaklan, Abrell and Neumann 2016). Furthermore, the risk of failing to reject the null hypothesis of a unit root in each price series may be high, because the time span of the time series data is short (Campbell and Perron 1991; Shiller and Perron 1985).

The specification of each univariate AR (1) model with a one-year lag requires several steps. First, an AR model with one lag is estimated for each price series, and then 1000 data points are simulated for each series. These simulated prices are then converted to yearly prices, and an AR (1) model is re-estimated to get adjusted AR coefficients. The estimated AR (1) model results are presented in Table (4-6).

Table 4-6: AR (1) Model Estimation

	Dependent Variable:		
	Wheat	Canola	Straw
	(1)	(2)	(3)
AR(1)	0.091***	0.158***	0.576***
	(0.031)	(0.031)	(0.026)
Intercept	246.099***	462.506***	47.475***
	(0.317)	(0.636)	(0.790)
Observations	1,000	1,000	1,000
Log Likelihood	−3,627.886	−4,247.672	−3,781.112
σ^2	82.921	286.415	112.612
Akaike Inf. Crit.	7,261.773	8,501.344	7,568.224
Note:			*p<0.1; **p<0.05; ***p<0.01

The corresponding AR (1) equations for wheat, canola, and wheat straw are, respectively:

$$p_{w,t+1} = 246.099 + 0.091p_{w,t} + \varepsilon_w \quad (4.11)$$

$$p_{c,t+1} = 462.506 + 0.158p_{c,t} + \varepsilon_c \quad (4.12)$$

$$p_{e,t+1} = 47.475 + 0.576p_{e,t} + \varepsilon_e \quad (4.13)$$

The results of the AR model estimations suggest that straw prices are relatively sticky across years compared to wheat and canola prices. The estimated AR parameter for the straw equation indicates that about half of this year's straw price is reflected in next year's straw price. On the other hand, the small AR parameters on the wheat and canola equations indicate that wheat and canola prices are more likely to fluctuate around their means. The estimated parameters and the standard errors are used to generate 9 wheat, canola, and wheat straw midpoints. Only 9 prices are used to reduce the length of time it takes to estimate the dynamic programming model. These midpoint values are then used to construct 729 (i.e. 9x9x9) unique price states, and a 729×729 price state probability transition matrix. The error terms in equations 4.11 - 4.13 are assumed to be independent. This matrix maps the probabilities of transitioning to any one of 729 price states, conditional on being in any one price state. The price midpoints for wheat, canola, and wheat straw used in the dynamic programming model are summarized in Table (4-7).

Table 4-7: Prices Used in the Dynamic Programming Model

Price	*Number of Obs.*	*Minimum*	*Maximum*	*Mean*
Wheat (CAD/t)	9	214.3785	242.1329	228.2557
Canola (CAD/t)	9	448.2203	510.5747	479.3975
Straw (CAD/t)	9	36.01511	67.44937	51.73224

4.2.8 Canola Disease

Canola is susceptible to disease that affects oilseed and biomass yield. Two of the most common canola diseases in Alberta are blackleg and clubroot. Blackleg is a fungus that causes the stem of the canola plant to rot, which impedes the nutrient and water uptake of the plant (The Government of Alberta n.d.). Similarly, clubroot is a fungus that germinates in the soil and primarily affects the root development of canola plants (The Government of Alberta n.d.). Depending on the severity of the disease, the yield loss associated with blackleg and clubroot in Alberta can range from 0 to 100% (Strelkov and Hwang 2014; Hwang et al. 2016). It is assumed that the average yield loss associated with canola disease is 30%. Therefore, when $d_t = 1$ canola yields are 70% of yields that occur when $d_t = 0$. The probability of contracting canola disease next year depends on whether there was canola disease present in the soil in the current year, and what crop was grown in the current year. These probabilities are therefore state dependent, and can be represented by a probability matrix. The canola disease probability matrix is presented in Table (4-8).

Table 4-8: Canola Disease State Transition Probabilities

		End State			
		Canola/No Disease	Canola/Disease	Wheat/No Disease	Wheat/Disease
Start State	Canola/No Disease	0.8	0.2	0.9	0.1
	Canola/Disease	0.4	0.6	0.7	0.3
	Wheat/No Disease	0.9	0.1	0.95	0.05
	Wheat/Disease	0.7	0.3	0.85	0.15

Data on the probability of contracting canola disease in Alberta is limited and depends on geographical location. In 2018, about 15% of surveyed canola fields across Alberta tested positive for clubroot (Strelkov et al. 2019). Information about what crop was grown and whether clubroot was present in the previous year for each field was not available. Therefore, it is assumed that (1) a farmer grew canola in 2018 only if there was no canola disease in 2017, and (2) half of the infected fields were previously under wheat and the other half were previously under canola. Therefore, if no canola disease is present, the probability of contracting canola disease next year if either canola or wheat was grown this year is 20% or 10%, respectively. It is suggested that farmers take a minimum two-year break from growing canola, or a four-year break in high risk areas, because canola diseases can survive in the soil for several years (Canola Council of Canada 2020; Canola Council of Canada n.d.; The Government of Alberta 2020). Therefore, the probabilities of contracting canola disease if wheat is grown are assumed to be half of the probabilities of contracting canola disease if canola was grown. For example, if canola or wheat was previously grown and there was canola disease, there is a 60% or 30% chance, respectively, that canola disease occurs next year if canola is grown. If canola or wheat was previously grown and there was no canola disease, there is a 10% and 5% chance, respectively, that canola disease occurs next year if wheat is grown.

There are a couple of things to note about the canola disease state and the transition probabilities. First, the canola disease state and state transition probabilities apply to all crop decisions, but the canola disease only effects canola yields. For example, if canola is grown next year and a canola disease is present in the current year, canola yields next year are less than if the canola disease was not present in the current year. If wheat is grown next year, wheat yields are not affected if canola disease occurs. Second, the assumed canola disease damage of 30% and the probabilities in Table (4-8) are just one possible representation of canola disease states in Alberta.

The severity of the canola disease damage and the probability of contracting canola disease could depend on the geographical location in Alberta and could change over time (Gabert 2018).

4.3 Results

The previous section defined the farmer's annual decision problem as one where the farmer makes crop and straw management decisions to maximize the value of land. The formulation in Equation 4.8 shows how these decisions are linked to state variables: SOM, surface residues, prices, and canola disease. This section examines the solution to the Bellman equation (see Equation 4.8) in detail with respect to three key areas of interest. First, how the value of farmland varies with SOM and residues is investigated. Second, how crop decisions vary with SOM and different crop and straw prices is investigated. Third, how decisions regarding the sale of wheat straw change for varying straw prices is investigated. The analysis starts in Section 4.3.1 by investigating these areas in the face of a stable long-term historical process that are used to generate a probability distribution of prices. However, it is important to consider how these three areas would change if there was a large demand for straw (due to the emergence of an ethanol industry), so Section 4.3.2 presents results where new increased prices are assumed to emerge from this new demand.

4.3.1 Results within the context of Historical Straw Prices

4.3.1.1 The Value of Farmland

The value function defined in Equation 4.8 represents the expected value of farmland under optimal management given the CDS, SOM, crop residue, and price state variables. Figure (4-6) shows estimates of the expected farmland values. SOM has a large impact on expected land value, as can be seen by the change in color gradient along the y axis. This result occurs because SOM directly affects crop yield, as shown in Figure (4-2). In contrast, amounts of crop residues have little impact on land value, which can be seen in Figure 6 by the lack of change to the color gradient along the x axis. Crop residues are important because they are eventually incorporated into SOM, but this process is not instantaneous, which limits the effect on land value. Furthermore, the stock of residues is small in comparison to the total stock of organic matter in the soil, especially at the higher SOM values. Figure 6 also shows that the expected value of farmland varies with the canola disease state. Land value immediately after growing wheat (CDS 3 and 4) is greater than after growing canola (CDS 1 and 2) for all SOM and crop residue ranges. This result is caused by a difference in probabilities of contracting canola disease, which are higher after canola is planted (see Table (4-8)).

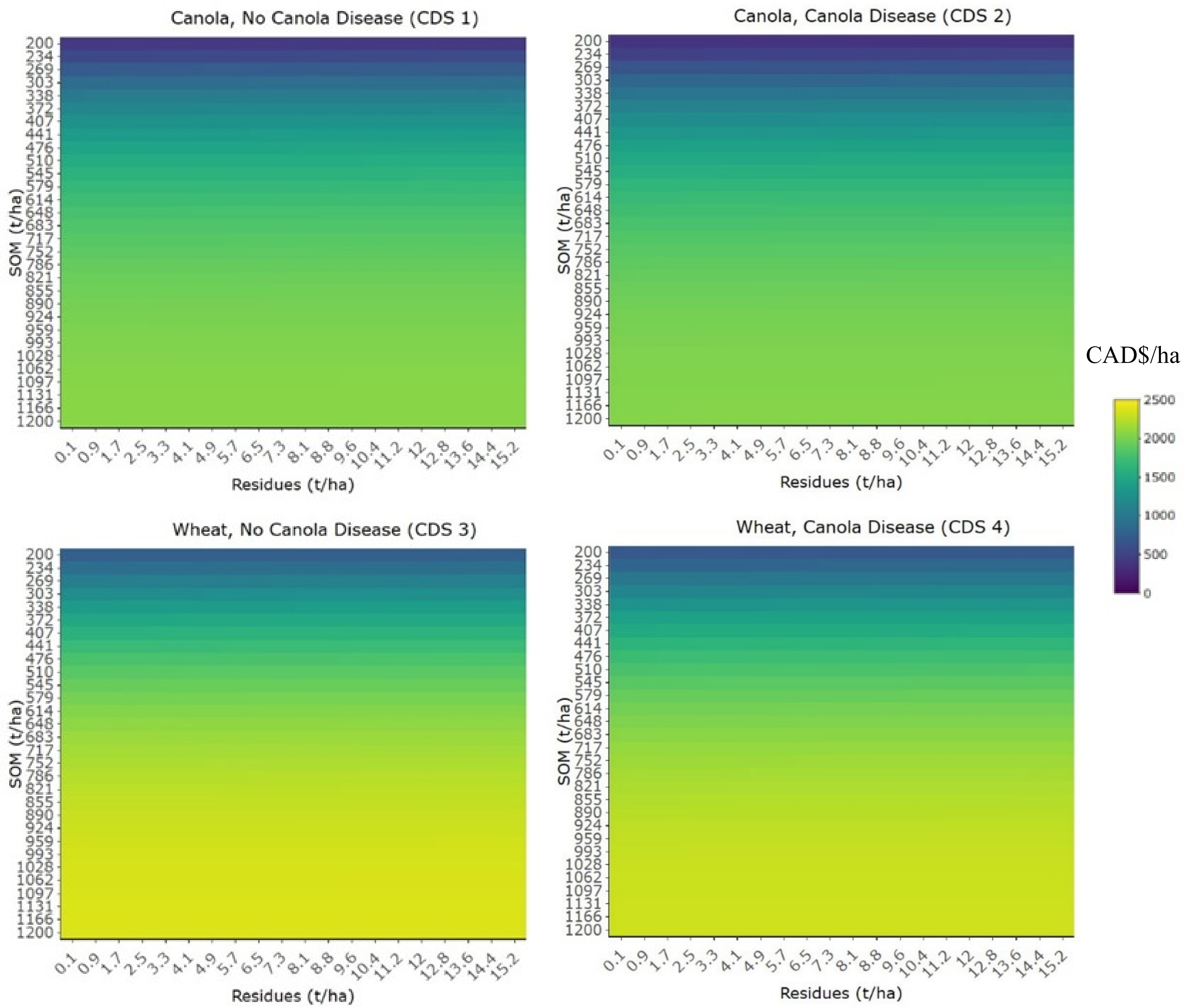

Figure 4-5: *Value of farmland for each canola disease state (CDS), SOM, and crop residue state combination. Wheat, canola, and straw prices are fixed at their means ($228.3, $479.4, and $51.7 per tonne, respectively).*

4.3.1.2 Crop Decisions

The value function is maximized with respect to the crop choice, H_t. To understand how these decisions change with the state variables, it is possible to examine the value of Equation 4.8 when the decisions are constrained to select each management option: (1) plant canola, (2) plant wheat, and (3) harvest straw given wheat was planted. Solving the Bellman equation generates unique value functions for each of these decisions which can then be compared to see how optimal decisions change with the state variables.

Figure (4-6) displays the value of farmland under wheat and canola when crop and straw prices are at their means. Crop residues add little to the value of farmland (as shown in Figure (4-5)) so it is held fixed at the mean, 8.1 t/ha. In the two left panels of Figure (4-6) (no canola disease), the land value under canola is greater than wheat for all levels of SOM. Therefore, the farmer always chooses canola when there is no previous canola disease, whether wheat (CDS 3) or canola (CDS 1) was grown previously. This is because the risk of contracting canola diseases is lower when no canola disease was previously present (see Table (4-8)). Conversely, the risk of contracting canola disease is higher if canola disease was previously present and if canola was the chosen crop the previous year (CDS 2). Under these conditions, the wheat choice dominates. In the case where the farm has a history of canola disease but wheat was grown in the previous year (CDS 4), the probability of canola disease is less than when last year's crop was canola (CDS 2), but more than if no canola disease was previously present (CDS 1 and 3). In this case (CDS 4), the optimal crop choice depends on the level of SOM, and somewhat on levels of residues. When SOM is low ($\leq$ 441 t/ha), the farmer's optimal crop choice is canola and when SOM is high ($\geq$ 441 t/ha), the optimal choice is wheat over a wide range of crop residues (0.1 to 12t/ha). The switch point in terms of SOM changes only slightly when crop residues are above 12t/ha to 407t/ha, for this case only (CDS 4).

Changes to crop or straw prices may affect the optimal crop decisions of a farmer, which in turn affects the value of farmland. Figure (4-7) plots the expected value of farmland under wheat and canola for varying wheat prices in CDS 4 (grew wheat/canola disease last year), where decisions are affected by wheat prices. A change to wheat prices relative to the other prices could affect the crop decision of a farmer. At mean prices (Panel (a)), in CDS 4 (grew wheat/canola disease last year) the value of growing canola is greater than wheat until SOM reaches about 450 t/ha. At this point the farmer switches from growing canola to growing wheat. The decision to grow wheat occurs at a lower SOM level when the price of wheat is high (407 t/ha in Panel (b) vs. 450 t/ha in Panel (a)), and the decision to grow wheat occurs at a higher SOM level when the price of wheat is low (465 t/ha in Panel (b) vs. 450 t/ha in Panel (a)).

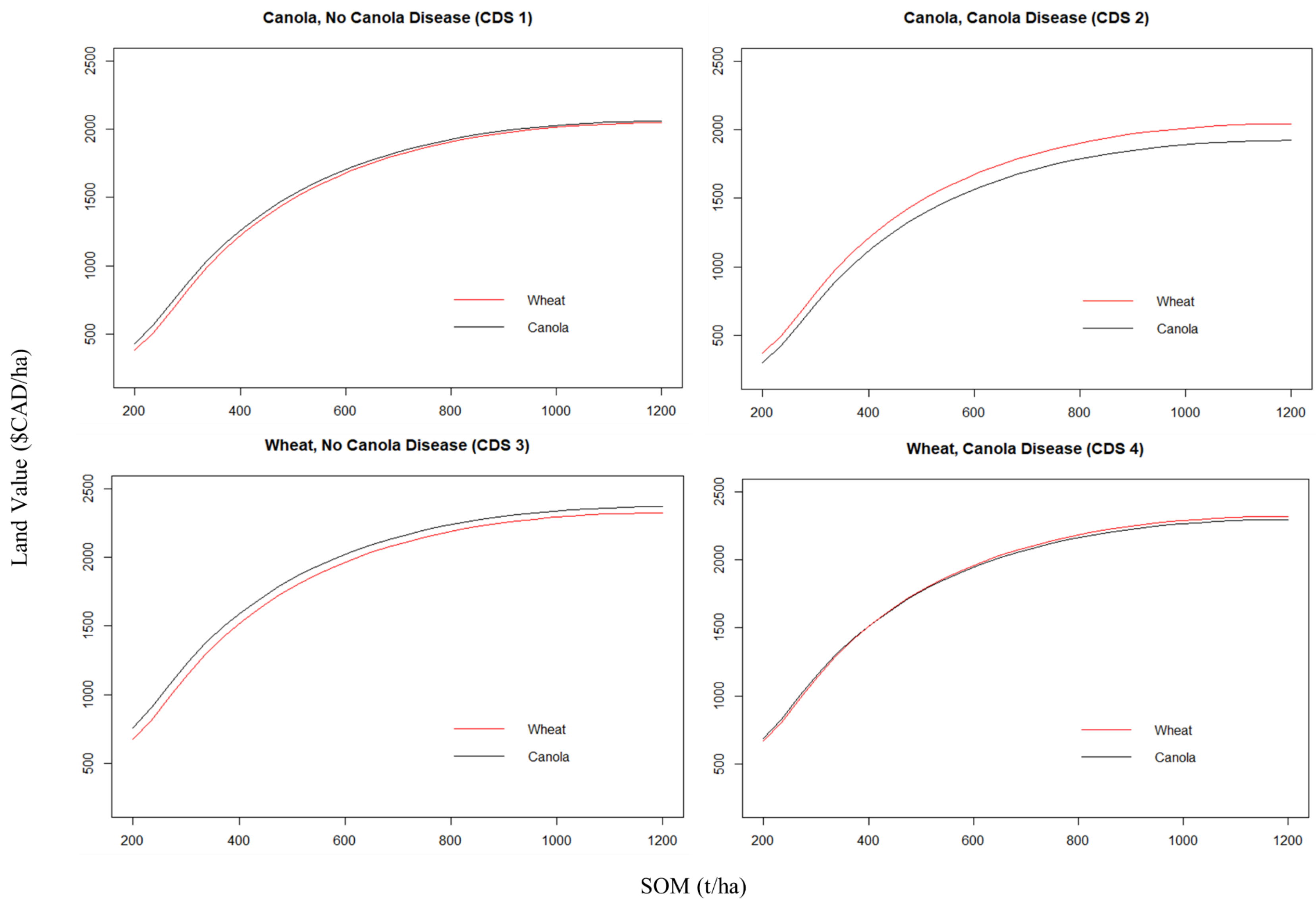

Figure 4-6: Value of farmland under wheat and canola. Wheat, canola, and straw prices are fixed at their means ($228.3, $479.4, and $51.7 per tonne, respectively). Crop residues are fixed at the mean (8.1 t/ha).

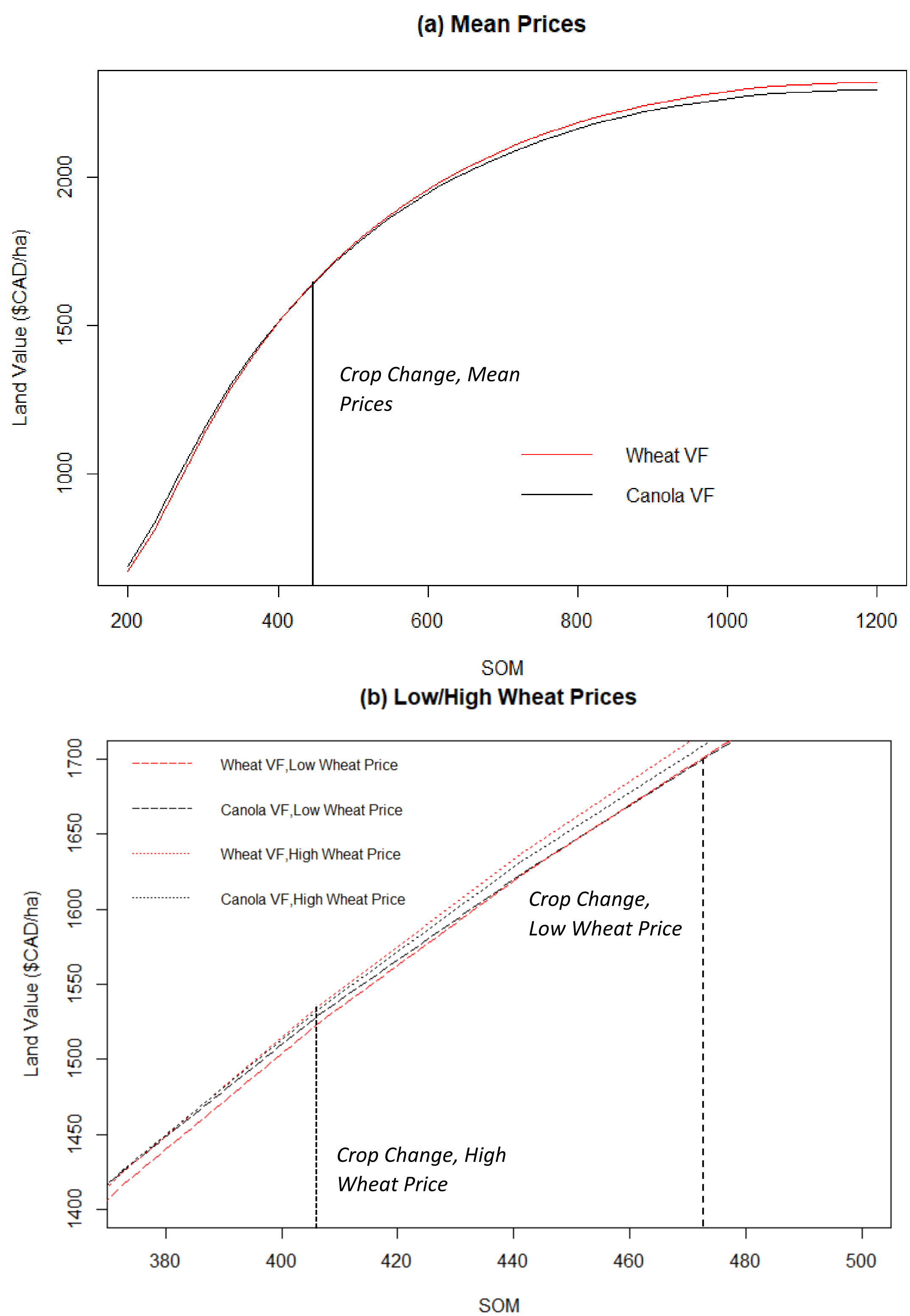

Figure 4- 7: Value of farmland with varying wheat prices for Canola Disease State (CDS) 4. Panel (a) is the value of farmland under wheat and canola when wheat, canola, and straw prices are fixed at their means ($228.3, $479.4, and $51.7 per tonne, respectively). Panel (b) is the value of land under wheat and canola when the price of wheat is low ($214.4/t) or high ($242.1/t). VF is the value of farmland.

Figure (4-8) plots the expected value of farmland under wheat and canola for varying canola prices in CDS 4 (grew wheat/canola disease last year), where decisions are affected by canola prices. When the price of canola increases the switch between canola and wheat shifts upwards to higher SOM levels (372 t/ha at point (a) vs. 540 t/ha at point C). The decision to grow canola occurs at a higher SOM level when the price of canola is high (540 t/ha at point C vs. 435 t/ha at point B), and the decision to grow wheat occurs at a lower SOM level when the price of canola is low (372 t/ha at point A vs. 450 t/ha at point C). The crop decision is more sensitive to canola prices than wheat prices in CDS 4 (grew wheat/canola disease last year).

The value of farmland and the crop decisions are also sensitive to wheat straw prices, but only when straw prices are above a certain level. This occurs because a farmer can observe the price before making the decision to sell or retain straw. In Figure (4-9), the crop choice effects on land value are shown for two different disease states: CDS 1 (grew canola/no canola disease last year and CDS 4 (grew wheat/canola disease last year). In CDS 4, wheat does not become the optimal crop until SOM is 372 t/ha. For CDS 1, wheat does not become the optimal crop until SOM is higher at 855 t/ha. The higher risk of canola disease in panel (c) than in panel (a) makes growing wheat the more attractive option. Crop residues add to the value of farmland because they decompose into the stock of SOM. In most of the previous examples, crop residues levels did not affect the crop decisions. However, crop residues do affect the decision when the price of wheat straw is high at $67/t. When residues are low the switch to wheat occurs at a higher SOM than when residues are high. The switch from canola to wheat occurs when SOM is between 752 and 890t/ha in panel (b) (grew canola/no canola disease last year). The switch between growing canola and growing wheat occurs when SOM is between 303 and 407 t/ha when the price of straw is at $67/t in panel (d) (grew wheat/disease last year).

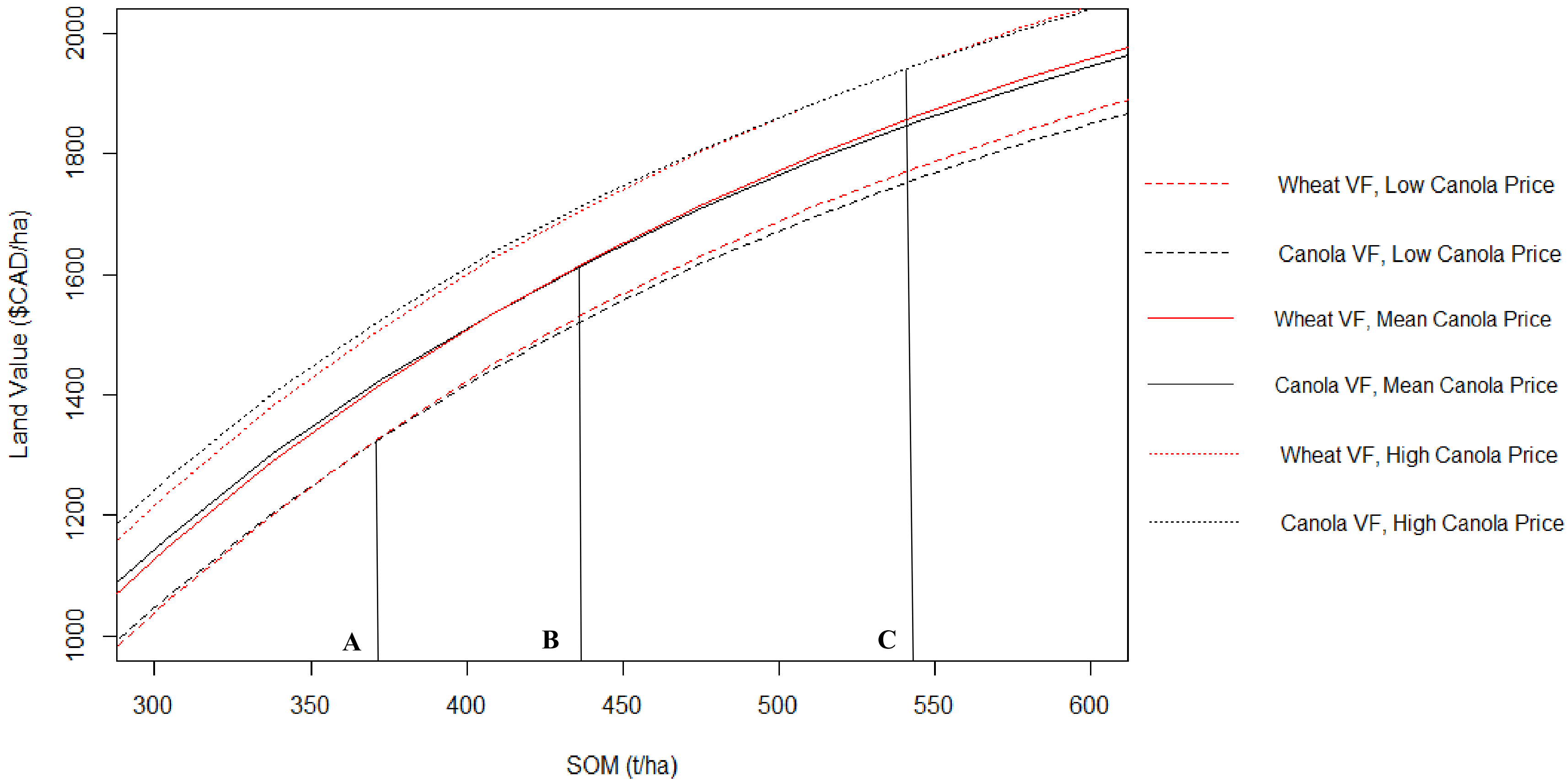

Figure 4-8: Value of farmland with varying canola prices for Canola Disease State (CDS) 4. The value of farmland under wheat and canola when wheat and straw prices are fixed at their means ($228.3 and $51.7 per tonne, respectively). The price of canola is low at point A ($448.2/t), average at point B ($479.4/t), and high at point C ($510.6/t). VF is the value of farmland.

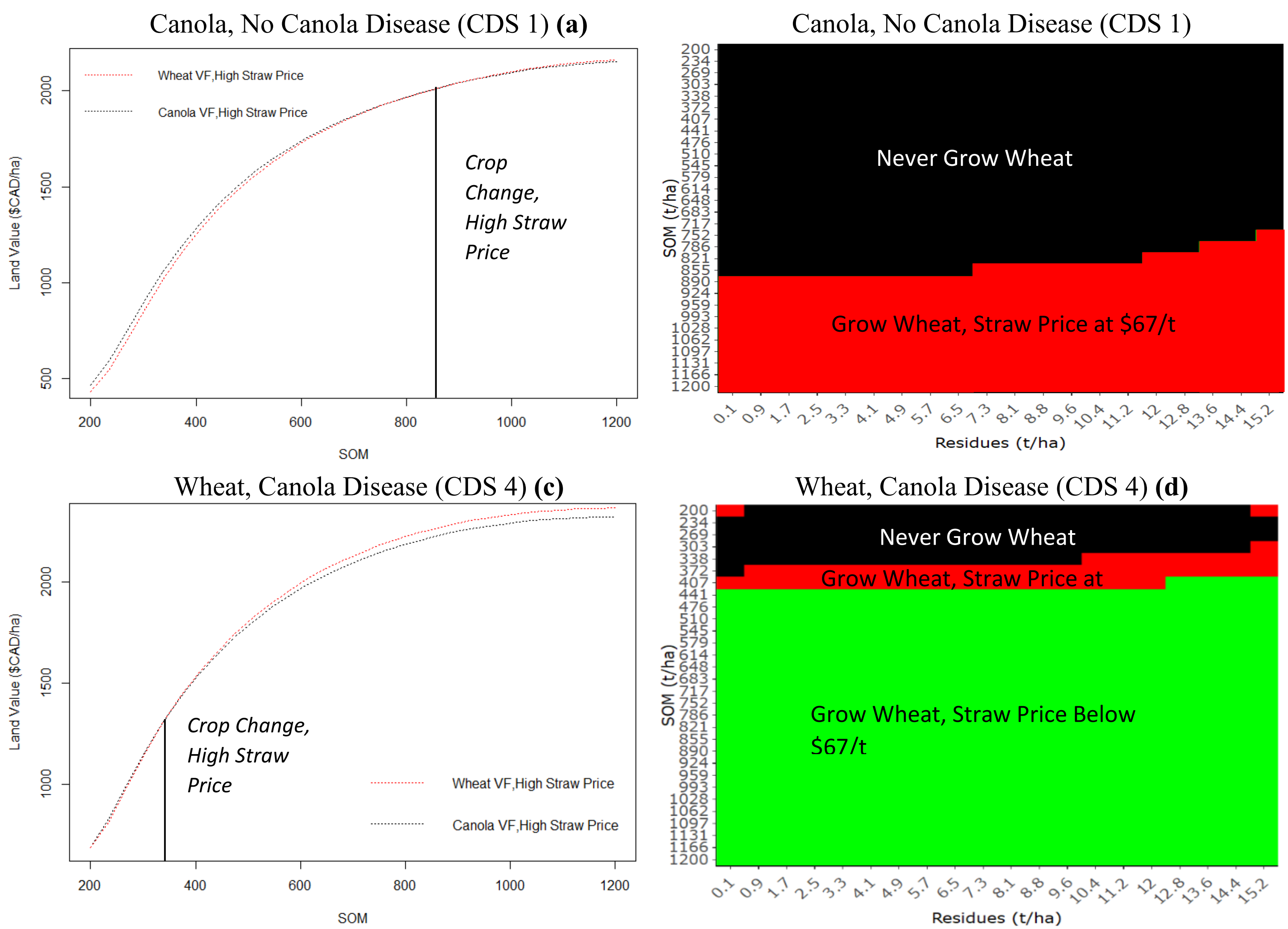

Figure 4-9: Value of farmland with varying wheat straw prices. Change to the value of farmland when the price of wheat straw is high ($67/t). The price of canola and wheat are held fixed at their means ($228.3 and $479.4 per tonne, respectively). The crop residue state in panel (a) and (c) are held fixed at 8.1 t/ha. VF is the value of farmland.

4.3.1.3 Decisions Regarding Sales of Wheat Straw

Figures (4-10) and (4-11) show optimal decisions regarding the sale of wheat straw when the price of wheat straw is \$63/t and \$67/t, respectively. Wheat straw is never harvested when there was no previous canola disease (CDS 1 and CDS 3) if the price of straw is 63\$/t, because wheat is not the optimal the crop choice at this price. Canola is more financially suitable for a farmer because the risk of canola disease is low. A farmer sells straw when the straw price is \$67/t, but only when SOM is high and when crop residues are high. In the disease state CDS 3 (grew wheat/no disease last year), wheat is never grown so straw is never harvested.

In the disease state CDS 2 (grew canola/disease last year), a farmer grows wheat but does not sell wheat straw when the price of straw is \$63/t and SOM is less than 545 t/ha[22]. As SOM increases, a farmer is more willing to sell straw when crop residue accumulation is high because SOM can be sustained. The straw harvest decision also depends on realized wheat yields (i.e. low, average, or high yields). Straw is sold at lower SOM ranges when wheat yields are low than if wheat yields are high. Note that results pertaining to harvesting straw when yields are low, average, or high depend on the cost structure of harvesting straw. With costs being incurred on a per unit basis, lower straw yields imply a lower total cost to harvesting straw. If the cost of harvesting straw were fixed (i.e. constant costs per hectare) this result would likely be nullified. When the price of wheat straw is \$67/t, wheat straw is always sold.

In CDS 4 (grew wheat/no disease last year), if the price of straw is \$63/t, canola is grown when SOM is ≤ 407t/ha and wheat is grown when SOM is ≥ 407 t/ha. A farmer harvests wheat straw at higher ranges of SOM (i.e. SOM > 545t/ha), but the decision also depends on the crop

[22] In Figure 4-10, the band at 200 t/ha SOM in CDS 2 that says to harvest straw at any wheat yield is an artifact of the model. Realistically, wheat is grown but straw is not be sold.

residue state. The higher the crop residue accumulation, the more willing a farmer is to sell straw because SOM levels can be sustained. When the price of straw is \$67/t, canola is grown when SOM $\leq$ 372 t/ha and when crop residue accumulation is low.

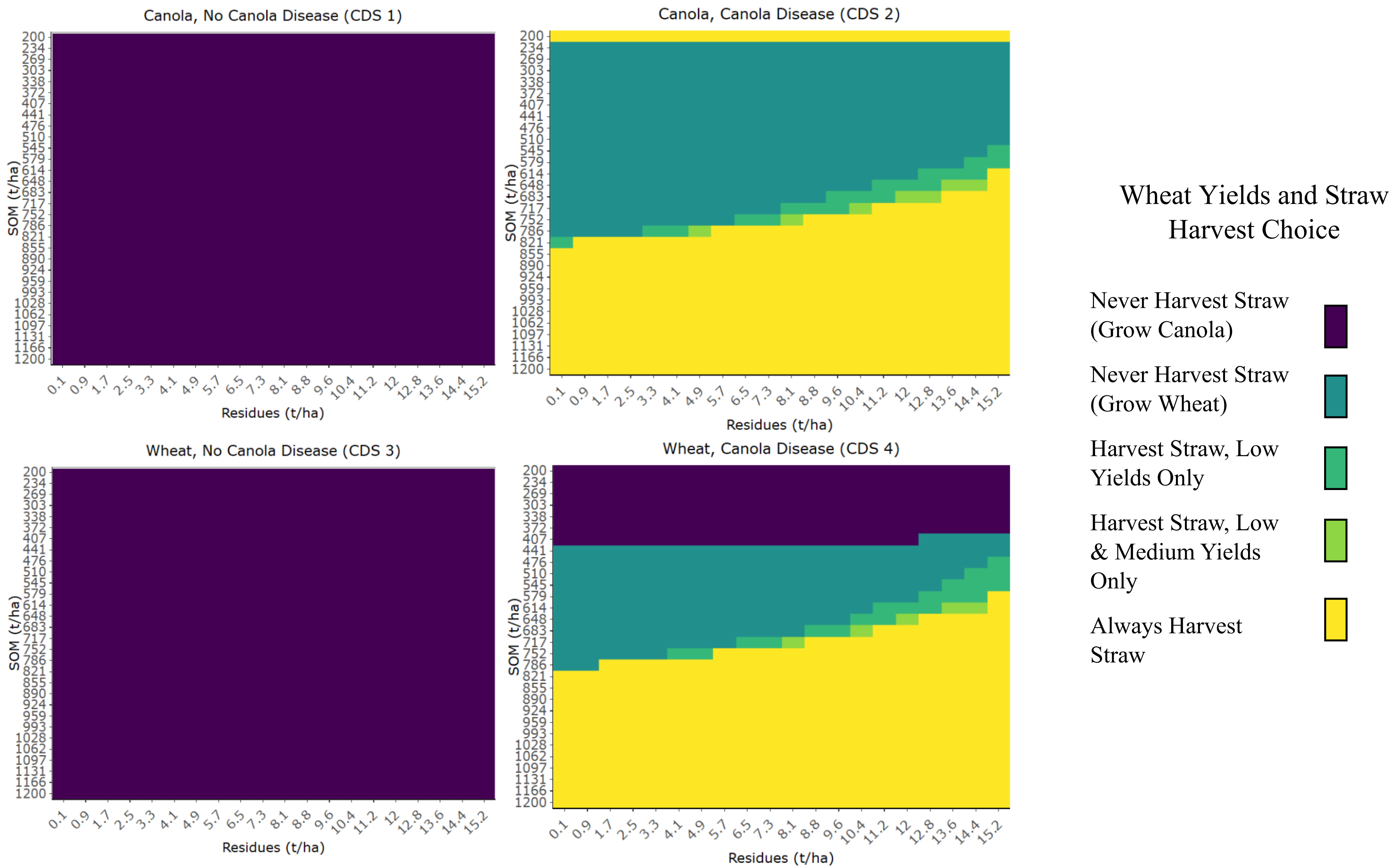

Figure 4-10: The decision to harvest wheat straw. The price of wheat and canola are fixed at their means ($228.3 and $51.7 per tonne, respectively), and the price of straw is $63.5/t.

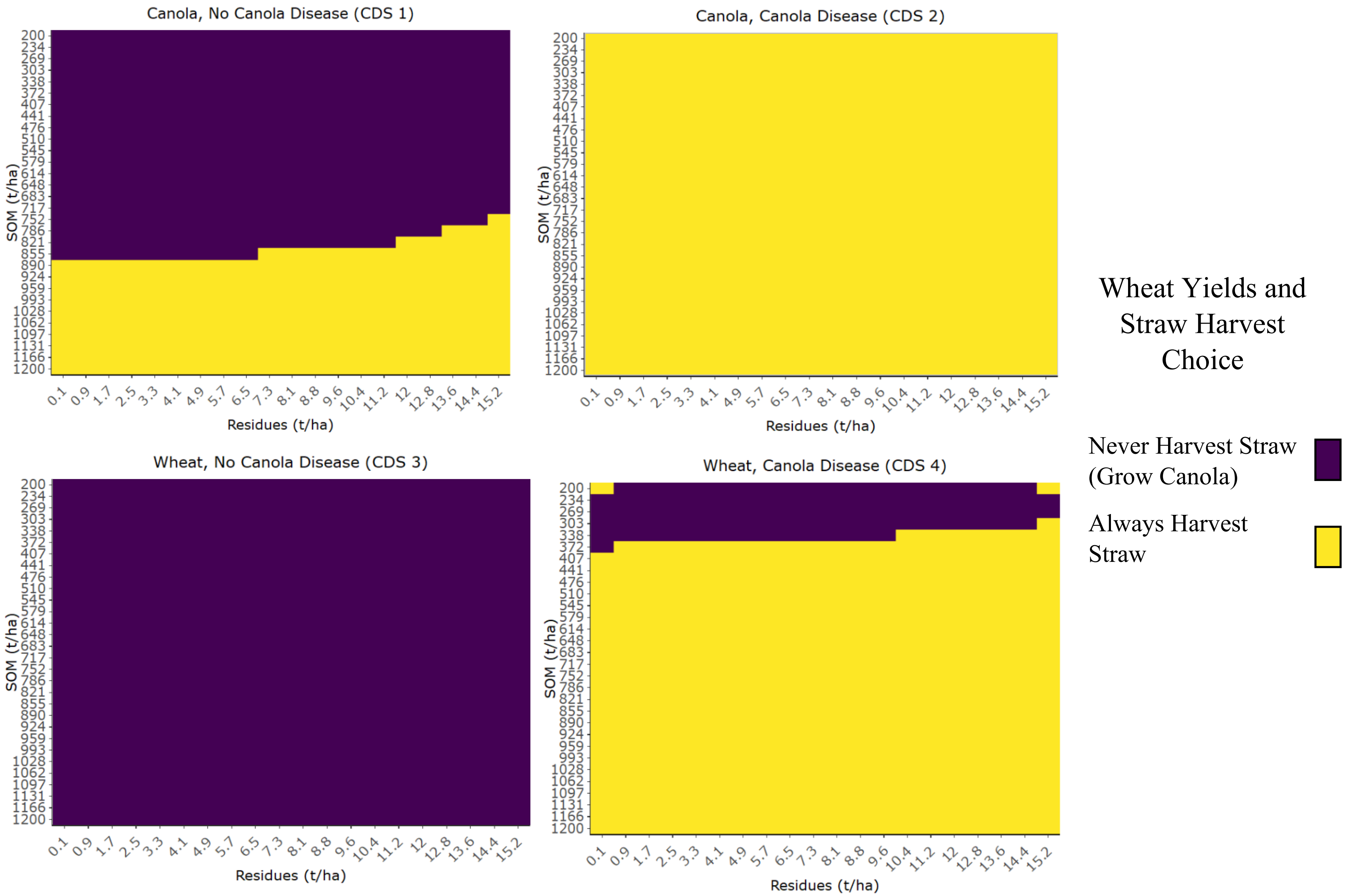

Figure 4-11: The decision to harvest wheat straw. The price of wheat and canola are fixed at their means ($228.3 and $51.7 per tonne, respectively), and the price of straw is $67.4/t.

4.3.2 Structural Price Change: Ethanol Producers

The presence of an ethanol producer may affect the price of wheat straw. Therefore, the mean price of wheat straw is increased by 20% to represent a situation where an ethanol producer wants to purchase large quantities of wheat straw. The variance of the price distribution could also change but the distribution that was used in Section 4.3.1 is maintained.

4.3.2.1 The Value of Farmland

With a 20% rise in the straw price, the new mean price is \$62.08 t/ha, which is slightly greater than the \$62/t break even price of straw. Therefore, the value of farmland is almost identical to the value of farmland under the old straw price regime when wheat, canola, and straw prices are fixed. For straw prices in the new straw price regime at or above the mean (i.e. \$62.08/t to \$77.79/t), the difference between the value of farmland under the new straw price regime and the value of farmland under the old straw price regime ranges from increases of 2% to 22%. These results are based on holding wheat and canola prices fixed, and depend on the CDS, SOM, and crop residue state combinations. The largest increases to the value of farmland occur for straw prices at \$77.79 t/ha, and in CDS 2 (grew canola/disease last year), with high SOM, and high crop residue states. These states are the most conducive for growing wheat.

4.3.2.2 Crop Decisions

The results in Section 4.3.1 showed that when straw prices reach the highest levels in their distribution, the farmer switches to wheat. This result becomes amplified with the increased price distribution. Figure (4-12) plots the farm management decision for select straw prices that are within the upper half of the new straw price distribution. In CDS 1 (grew canola/no disease last year), when SOM is low (i.e. $\leq$ 372 t/ha), canola is grown. As SOM and crop residues increase, the required straw price for a farmer to grow wheat and sell straw decreases. This result occurs because crop residues are needed less to grow and maintain SOM. Results are similar in CDS 3 (grew wheat/no disease last year), however higher straw prices (i.e. $74-$78/t) are needed for all crop residue and SOM states for a farmer to grow wheat and sell straw. The presence or absence of canola disease and the straw price have a combined effect on the straw selling decision. In general, if canola disease occurred in the past, lower straw prices are required to harvest wheat straw for a given SOM. Moreover, lower straw prices are generally required for a farmer to sell straw at the same SOM level, if canola disease was not present (CDS 1 and CDS 3), than if canola disease was previously present (CDS 2 and 4). This result occurs because a high risk of canola disease makes growing wheat a more attractive option than canola which leads to more opportunities to harvest wheat straw.

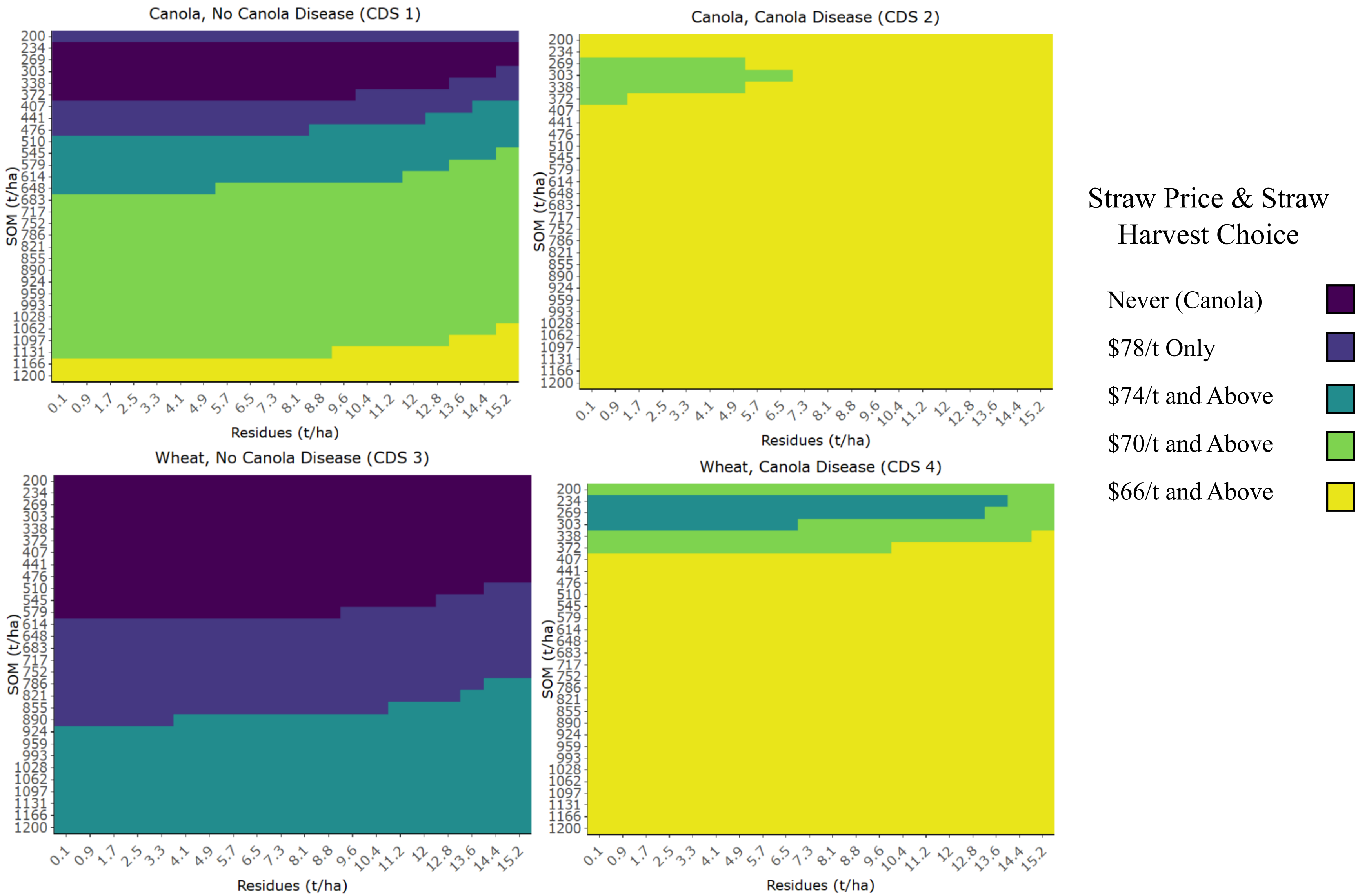

Figure 4-12: When to Harvest Wheat Straw with a Structural Change in Wheat Straw Prices (prices are within the upper half of the new straw price distribution).

4.3.2.3 Decisions Regarding Sales of Wheat Straw

To further investigate wheat straw sales, we allow mean straw prices to vary between \$63/t and \$99/t in \$1 increments. This process allows us to draw a relationship between wheat straw price, the SOM level, and the decision to harvest wheat straw. To do this, the model is solved 37 times, each time with a new mean straw price and associated straw price distribution. Figure (4-13) plots the minimum straw price, recorded in the fall, for each SOM state that is required for a farmer to sell wheat straw.

The dotted vertical line represents the marginal cost of harvesting wheat straw (i.e. \$62/t). A farmer would never sell straw if the price of straw were equal to or lower than the marginal harvest cost. However, wheat straw is available at \$64/t if canola disease was present last year (CDS 2 and 4) when SOM is between 900 and 1200 t/ha. In general, the required price to sell straw is higher when SOM is low. The space underneath the curves represents SOM/price combination where wheat straw is not sold, and the space on and above the curve represent SOM/price combinations where wheat straw is sold. Higher straw prices are required to sell straw if there is no canola disease present. This is because the value of land when there is disease decreases proportionately more for land at higher SOM than lower SOM. There is a downward shift to the opportunity cost of harvesting straw when disease is present. As a result, an ethanol producer may need to pay a price premium on top of the marginal cost of harvesting straw especially if SOM is low. For example, straw is available at \$64/t in CDS 2 (grew canola/disease last year), and at \$70/t in CDS 3 (grew canola/no disease last year) when SOM is about 700 t/ha.

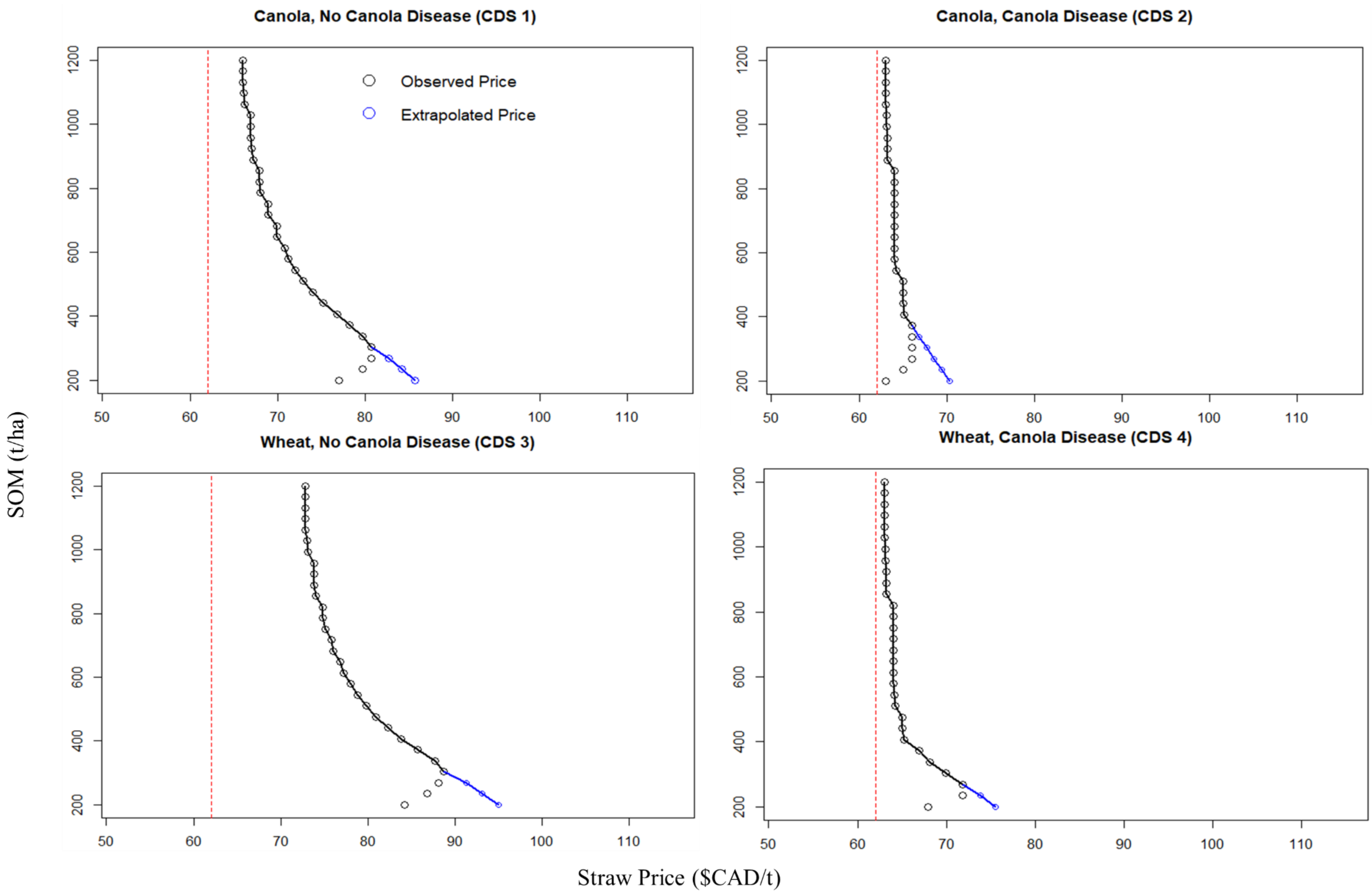

Figure 4-13: The minimum required straw price for each SOM level that is needed for a farmer to grow wheat and sell wheat straw. Wheat and canola prices are held fixed at their means, and the crop residue state is fixed at the mean. The blue points are linear extrapolations of the relationship between SOM and the price of wheat straw required for a farmer to sell wheat straw.

4.4 Conclusions

Understanding the conditions that influence whether farmers are willing to sell wheat straw gives some information about the potential supply of wheat straw as a future biofuel feedstock. Moreover, changes to these conditions can cause available supplies to change. These dynamics are particularly important because feedstock variability has been cited as being a major barrier to the emergence of cellulosic ethanol industries worldwide (Chen and Smith 2017; Padella, O'Connell and Prussi 2019). This analysis identifies several factors that, are important in informing the straw procurement strategy of second-generation ethanol producers.

4.4.1 Farmer Decision Making

Results suggest that the optimal crop choice of farmers and the supply of wheat straw is likely to fluctuate from year-to-year, influenced by several changing factors. First is the potential for canola disease, which is influenced by the currently existing crops. A farmer grows wheat when the risk of canola disease is high because the difference between expected wheat and canola yields makes wheat the more financially attractive option when wheat, canola, and straw prices are at their means. However, growing wheat makes canola a more desirable crop choice in subsequent years because the risk of contracting canola disease decreases.

A second intervening factor is SOM. The risk of canola disease, along with the SOM level, may affect the crop choice. Wheat is grown when SOM levels are high, and canola is grown when SOM levels are low. This is because: (1) the decomposition rate of canola residues is greater than wheat, and (2) canola produces more residues per tonne of oilseed than wheat produces per tonne of grain. Together, (1) and (2) imply that SOM can be accumulated faster if canola is grown which, in turn, leads to attainment of higher crop yields sooner. If the canola disease risk and SOM level incent a farmer to grow wheat, the propensity of the farmer to sell wheat straw depends on the current and future value of wheat straw. Specifically, if the immediate profits from selling wheat straw does not exceed the loss to the future value of farmland from lower crop residues and potentially lower SOM, a farmer does not sell straw.

4.4.2 Implications for Ethanol Producers

Results from the crop and straw management decisions of farmers can be used by prospective ethanol producers in several ways to provide insights into procuring wheat straw. First, producers could consider procuring straw in Alberta where wheat is grown most frequently. Wheat is grown most frequently when the risk of canola disease is high and SOM levels are high. In this environment, wheat straw may (1) be available for purchase at a lower price, and (2) may be available in larger quantities since wheat yields are high. However, the supply of straw may be still variable because of fluctuating crop prices and because farmers want to build up SOM. If ethanol producers establish in an area where canola is grown more frequently, there may be more variability in (1) quantity of supply because of rotating crops (although this will be mitigated by averaging the crop proportions over larger supply areas) and (2) the price at which farmers are willing to sell straw, which is affected by the presence/absence of canola disease.

Results also indicate that producers would want farmer's net price (i.e. the difference between the unit price and the unit cost) expectations of wheat to be consistently high compared to canola. This would ensure that growing wheat is financially attractive choice every year. It is important to note that the data used in this analysis indicates that the ratio of the net price of wheat to canola is different across the province for different soil zones. Furthermore, the supply of wheat straw could be less variable if producers can offer high straw prices. For example, results indicate that wheat straw can be bought for about $95/t for all SOM levels when the risk of canola disease is low. When the risk of canola disease is high, wheat straw can be bought for about $70/t for all

SOM levels. This is mixed news for prospective ethanol producers. On the one hand, it implies that ethanol producers can influence the supply of wheat straw if they are willing to pay a higher price. However, paying a high straw price could be detrimental to the financial position of a producer.

Chapter 5: Conclusions

The goal of this thesis is to investigate regional and international factors that could influence the future success of a second-generation ethanol industry in Canada. Chapters 2 and 3 are macro-level investigations into the price relationships between markets related to the first-generation ethanol industry and the price of Canadian wheat grain. The price of Canadian wheat grain is included to represent a market that may be closely linked to the supply of wheat straw.

Short-run price dynamics in the wheat and ethanol markets could be affected by price changes in other markets. Second-generation producers could benefit from increasing output prices without the added consequence of having to pay higher feedstock costs. However, a decrease to corn prices means that ethanol prices follow. The price of wheat and ethanol change week-to-week if there is a shock to the equilibrium price relationship with corn and gasoline. A shock to the equilibrium system that causes wheat prices to adjust to a new equilibrium price may affect the decision of farmers to grow wheat. In turn, the supply of wheat straw could change. Second-generation ethanol producers may experience higher or lower profits if a shock to the equilibrium system forces ethanol prices to increase or decrease in the short-run. These results suggest that investors and policy makers ought to consider strategies that counteract unfavourable price movements in related markets that affect prices pertaining to the second-generation ethanol industry.

Price relationships are further explored in Chapter 2 by estimating dynamic correlations between each market. The supply of wheat straw and output price of ethanol could follow changes to the US corn price, which may be a significant source of price risk for producers. Furthermore, there could be situations where the price of ethanol is high and wheat straw supply is high. However, capacity constraints in the short run could prevent second-generation ethanol producers from taking advantage of high output prices by increasing production. There could also be situations where the price of ethanol is low, and the supply of wheat straw is low. In this case, ethanol producers may cut their production. Another important result is that major disruptions to the economy may influence several markets at once that are important to second-generation ethanol producers. For example, relationships were relatively strong during the financial crisis (2008-2009) and the pairwise relationships involving ethanol tended to be volatile during a period of agricultural price volatility and renewable fuels policy uncertainty (2013-2014). These relationships could likely change in the future if a second-generation ethanol industry develops.

The periods that corresponded to volatile market relationships in Chapter 2 generally corresponded to the structural breaks that were discovered in the BEKK-MGARCH model in Chapter 3. After controlling for structural breaks, price volatility in the feedstock and output markets may not be vulnerable to price shocks to any market, but volatility that persists in the wheat market could also persist in the ethanol market. The lack of significant price shock transmission effects among markets related to the first-generation ethanol industry may reflect current risk management strategies of first-generation ethanol producers. Prospective second-generation ethanol producers could consider adopting similar risk management approaches to hedge against unfavourable movements to wheat straw prices.

Chapters 2 and 3 operate under the assumption that the price of wheat grain could be related to the supply of wheat straw. Chapter 4 of this thesis expands on this idea by undertaking a micro-level investigation into how crop and straw prices are likely to influence the supply of wheat straw.

The availability of wheat straw given the current straw price regime could be highly variable form year-to-year, at least at the farm level. Given how the model was parameterized, the probability of contracting canola disease informs the optimal crop choice; when the probability is low (high), canola (wheat) is the dominant option. For certain canola disease risk probabilities, high or low expected wheat prices relative to expected canola prices encourage a farmer to switch from growing canola to wheat. If wheat is grown, the farmer has the option to sell straw in the fall after observing straw prices. The decision to sell straw then depends on whether the immediate profits form selling straw are greater than the loss to the future value of farmland from having lower crop residues on the soil surface that accumulate SOM. However, an important result pertaining to prospective ethanol producers is that offering high enough straw prices could ensure that straw is available on a consistent basis. This result is within the context that farmers trade off harvesting wheat straw against the value of building up SOM. When the risk of contracting canola disease is low, ethanol producers may be able purchase wheat straw (no matter what the SOM level is) at a price of about $95/t. When the risk of contracting canola disease is high, ethanol producers may be able to purchase wheat straw (no matter what the SOM level is) at a price of about $70/t.

The emergence of a second-generation ethanol industry depends on the future profitability of producers, which is likely to be affected by commodity price relationships and the supply of feedstock over time. Therefore, the results from this thesis may be used by prospective producers and policymakers to develop strategies to ensure the future success of a second-generation ethanol industry in Canada.

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Appendix 1: Calculation of Dynamic Correlations

$$R_t = Q_t^{\circ -1/2} Q_t Q_t^{\circ -1/2} \quad (2.3)$$

In matrix form, Equation 2.3 can be represented as the following:

$$\begin{pmatrix} 1 & \rho_{wg,t} & \rho_{we,t} & \rho_{wg,t} \\ \rho_{cw,t} & 1 & \rho_{ce,t} & \rho_{cg,t} \\ \rho_{ew,t} & \rho_{ec,t} & 1 & \rho_{eg,t} \\ \rho_{gw,t} & \rho_{gc,t} & \rho_{ge,t} & 1 \end{pmatrix} =$$

$$\begin{pmatrix} \frac{1}{h_{w,t}} & 0 & 0 & 0 \\ 0 & \frac{1}{h_{c,t}} & 0 & 0 \\ 0 & 0 & \frac{1}{h_{e,t}} & 0 \\ 0 & 0 & 0 & \frac{1}{h_{g,t}} \end{pmatrix} \begin{bmatrix} {h_{w,t}}^2 & h_{wc,t} & h_{we,t} & h_{wg,t} \\ h_{cw,t} & {h_{c,t}}^2 & h_{ce,t} & h_{cg,t} \\ h_{ew,t} & h_{ec,t} & {h_{e,t}}^2 & h_{eg,t} \\ h_{gw,t} & h_{wgct} & h_{ge,t} & {h_{gt}}^2 \end{bmatrix} \begin{pmatrix} \frac{1}{h_{w,t}} & 0 & 0 & 0 \\ 0 & \frac{1}{h_{c,t}} & 0 & 0 \\ 0 & 0 & \frac{1}{h_{e,t}} & 0 \\ 0 & 0 & 0 & \frac{1}{h_{g,t}} \end{pmatrix}$$

Where, $\rho_{12,t}$ is the correlation between series 1 and 2 in period, t, ${h_{1,t}}^2$ is the variance of series 1 in period, t, and $h_{12,t}$ is the covariance of series 1 and 2 in period, t. Simplifying above yields the following:

$$\begin{pmatrix} 1 & \rho_{wg,t} & \rho_{we,t} & \rho_{wg,t} \\ \rho_{cw,t} & 1 & \rho_{ce,t} & \rho_{cg,t} \\ \rho_{ew,t} & \rho_{ec,t} & 1 & \rho_{eg,t} \\ \rho_{gw,t} & \rho_{gc,t} & \rho_{ge,t} & 1 \end{pmatrix} = \begin{pmatrix} 1 & \frac{h_{wc,t}}{h_{w,t}h_{c,t}} & \frac{h_{we,t}}{h_{w,t}h_{e,t}} & \frac{h_{wg,t}}{h_{w,t}h_{g,t}} \\ \frac{h_{cw,t}}{h_{c,t}h_{w,t}} & 1 & \frac{h_{ce,t}}{h_{c,t}h_{e,t}} & \frac{h_{cg,t}}{h_{c,t}h_{g,t}} \\ \frac{h_{ew,t}}{h_{e,t}h_{w,t}} & \frac{h_{ec,t}}{h_{e,t}h_{c,t}} & 1 & \frac{h_{eg,t}}{h_{e,t}h_{g,t}} \\ \frac{h_{gw,t}}{h_{g,t}h_{w,t}} & \frac{h_{gc,t}}{h_{g,t}h_{c,t}} & \frac{h_{ge,t}}{h_{g,t}h_{e,t}} & 1 \end{pmatrix}$$

Therefore, the time-varying correlations between any two series can be calculated as:

$$\rho_{12,t} = \frac{h_{12,t}}{h_{1,t}h_{2,t}}$$

Appendix 2: Matrix Representation of the DCC-MGARCH Model

Equation 2.5.1 presents the VECM in vector notation. Each parameter has a subscript that corresponds to one of the four price series (i.e. w = wheat, c = corn, e = ethanol, g = gasoline). The first subscript identifies the equation that the parameter belongs to. The second subscript for the β parameters identifies the effect. For example, $\beta_{c,w}$ represents the short-run effect on wheat price changes on corn price changes. The t and $t-1$ subscripts are time subscripts.

$$\begin{bmatrix} \Delta p_{w,t} \\ \Delta p_{c,t} \\ \Delta p_{e,t} \\ \Delta p_{g,t} \end{bmatrix} = \begin{bmatrix} \alpha_w \\ \alpha_c \\ \alpha_e \\ \alpha_g \end{bmatrix} + \begin{bmatrix} \beta_{w,w} & \beta_{w,c} & \beta_{w,e} & \beta_{w,g} \\ \beta_{c,w} & \beta_{c,c} & \beta_{c,e} & \beta_{c,g} \\ \beta_{e,w} & \beta_{e,c} & \beta_{e,e} & \beta_{e,g} \\ \beta_{g,w} & \delta_{g,c} & \beta_{g,e} & \beta_{g,g} \end{bmatrix} \begin{bmatrix} \Delta p_{w,t-1} \\ \Delta p_{c,t-1} \\ \Delta p_{e,t-1} \\ \Delta p_{g,t-1} \end{bmatrix} + \begin{bmatrix} \theta_w \\ \theta_c \\ \theta_e \\ \theta_g \end{bmatrix} \left([\mu_w, \mu_c, \mu_e, \mu_g] \begin{bmatrix} p_{w,t-1} \\ p_{c,t-1} \\ p_{e,t-1} \\ p_{g,t-1} \end{bmatrix} \right) + \begin{bmatrix} \varepsilon_{w,t} \\ \varepsilon_{c,t} \\ \varepsilon_{e,t} \\ \varepsilon_{g,t} \end{bmatrix} \tag{2.5.1}$$

Equation 2.6.1 represents the error process of the VECM in vector notation. The L parameters are the elements that are obtained through a Cholesky factorization of the $K \times K$ matrix of conditional variances, H_t.

$$\begin{bmatrix} \varepsilon_{w,t} \\ \varepsilon_{c,t} \\ \varepsilon_{e,t} \\ \varepsilon_{g,t} \end{bmatrix} = \begin{bmatrix} L_{11} & 0 & 0 & 0 \\ L_{21} & L_{22} & 0 & 0 \\ L_{31} & L_{32} & L_{33} & 0 \\ L_{41} & L_{42} & L_{43} & L_{44} \end{bmatrix} \begin{bmatrix} v_{w,t} \\ v_{c,t} \\ v_{e,t} \\ v_{g,t} \end{bmatrix} \tag{2.6.1}$$

Equation 2.7.1 is the equation for the time-varying covariance matrix in vector notation. The diagonal elements of the time-varying covariance matrix are the variances of each market in period t, and the off-diagonal elements are the covariances in period t.

$$\begin{bmatrix} {h_{w,t}}^2 & h_{w,t}h_{c,t}\rho_{wc,t} & h_{w,t}h_{e,t}\rho_{we,t} & h_{w,t}h_{g,t}\rho_{wg,t} \\ h_{c,t}h_{w,t}\rho_{cw,t} & {h_{c,t}}^2 & h_{c,t}h_{e,t}\rho_{ce,t} & h_{c,t}h_{g,t}\rho_{cg,t} \\ h_{e,t}h_{w,t}\rho_{ew,t} & h_{e,t}h_{c,t}\rho_{ec,t} & {h_{e,t}}^2 & h_{e,t}h_{g,t}\rho_{eg,t} \\ h_{g,t}h_{w,t}\rho_{gw,t} & h_{g,t}h_{c,t}\rho_{gc,t} & h_{g,t}h_{e,t}\rho_{ge,t} & {h_{gt}}^2 \end{bmatrix}$$

$$= \begin{bmatrix} h_{w,t} & 0 & 0 & 0 \\ 0 & h_{c,t} & 0 & 0 \\ 0 & 0 & h_{e,t} & 0 \\ 0 & 0 & 0 & h_{g,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_{wg,t} & \rho_{we,t} & \rho_{wg,t} \\ \rho_{cw,t} & 1 & \rho_{ce,t} & \rho_{cg,t} \\ \rho_{ew,t} & \rho_{ec,t} & 1 & \rho_{eg,t} \\ \rho_{gw,t} & \rho_{gc,t} & \rho_{ge,t} & 1 \end{bmatrix} \begin{bmatrix} h_{w,t} & 0 & 0 & 0 \\ 0 & h_{c,t} & 0 & 0 \\ 0 & 0 & h_{e,t} & 0 \\ 0 & 0 & 0 & h_{g,t} \end{bmatrix} \tag{2.7.1}$$

Appendix 3: Variance Equations of the BEKK Model

$$Wheat = C_{ww}^2 + A_{ww}^2 u_{w,t-1}^2 + A_{cw}^2 u_{c,t-1}^2 + A_{ew}^2 u_{e,t-1}^2 + A_{gw}^2 u_{g,t-1}^2 + 2A_{1w}A_{cw}u_{w,t-1}u_{c,t-1}$$
$$+ 2A_{ww}A_{ew}u_{w,t-1}u_{e,t-1} + 2A_{cw}A_{ew}u_{c,t-1}u_{e,t-1} + 2A_{ww}A_{gw}u_{w,t-1}u_{g,t-1}$$
$$+ 2A_{cw}A_{gw}u_{c,t-1}u_{g,t-1} + 2A_{ew}A_{gw}u_{e,t-1}u_{g,t-1} + B_{ww}^2\sigma_{w,t-1}^2 + B_{cw}^2\sigma_{c,t-1}^2 + B_{ew}^2\sigma_{e,t-1}^2$$
$$+ B_{gw}^2\sigma_{g,t-1}^2 + 2B_{ww}B_{cw}\sigma_{wc,t-1} + 2B_{ww}B_{ew}\sigma_{we,t-1} + 2B_{ww}B_{gw}\sigma_{wg,t-1} + 2B_{cw}B_{ew}\sigma_{ce,t-1}$$
$$+ 2B_{cw}B_{gw}\sigma_{cg,t-1} + 2B_{ew}B_{gw}\sigma_{eg,t-1}$$

$$Corn = C_{cw}^2 + C_{cc}^2 + A_{wc}^2 u_{w,t-1}^2 + A_{cc}^2 u_{c,t-1}^2 + A_{ec}^2 u_{e,t-1}^2 + A_{gc}^2 u_{g,t-1}^2 + 2A_{wc}A_{cc}u_{w,t-1}u_{c,t-1}$$
$$+ 2A_{wc}A_{ec}u_{w,t-1}u_{e,t-1} + 2A_{cc}A_{ec}u_{c,t-1}u_{e,t-1} + 2A_{wc}A_{gc}u_{w,t-1}u_{g,t-1} + 2A_{cc}A_{gc}u_{c,t-1}u_{g,t-1}$$
$$+ 2A_{ec}A_{gc}u_{e,t-1}u_{g,t-1} + B_{wc}^2\sigma_{w,t-1}^2 + B_{cc}^2\sigma_{c,t-1}^2 + B_{ec}^2\sigma_{e,t-1}^2 + B_{gc}^2\sigma_{g,t-1}^2 + 2B_{wc}B_{cc}\sigma_{wc,t-1}$$
$$+ 2B_{wc}B_{ec}\sigma_{we,t-1} + 2B_{wc}B_{gc}\sigma_{wg,t-1} + 2B_{cc}B_{ec}\sigma_{ce,t-1} + 2B_{cc}B_{gc}\sigma_{cg,t-1} + 2B_{ec}B_{gc}\sigma_{eg,t-1}$$

$$Ethanol = C_{ew}^2 + C_{ec}^2 + C_{ee}^2 + A_{we}^2 u_{w,t-1}^2 A_{ce}^2 u_{c,t-1}^2 + A_{ee}^2 u_{e,t-1}^2 + A_{ge}^2 u_{g,t-1}^2 + 2A_{we}A_{ce}u_{w,t-1}u_{c,t-1}$$
$$+ 2A_{we}A_{ee}u_{w,t-1}u_{e,t-1} + 2A_{we}A_{ge}u_{w,t-1}u_{g,t-1} + 2A_{ce}A_{ee}u_{c,t-1}u_{e,t-1} + 2A_{ce}A_{ge}u_{c,t-1}u_{g,t-1}$$
$$+ 2A_{ee}A_{ge}u_{e,t-1}u_{g,t-1} + B_{we}^2\sigma_{w,t-1}^2 + B_{ce}^2\sigma_{c,t-1}^2 + B_{ee}^2\sigma_{e,t-1}^2 + B_{ge}^2\sigma_{g,t-1}^2 + 2B_{we}B_{ce}\sigma_{wc,t-1}$$
$$+ 2B_{we}B_{ee}\sigma_{we,t-1} + 2B_{we}B_{ge}\sigma_{wg,t-1} + 2B_{ce}B_{ee}\sigma_{ce,t-1} + 2B_{ce}B_{ge}\sigma_{cg,t-1} + 2B_{ee}B_{ge}\sigma_{eg,t-1}$$

$$Gasoline = C_{gw}^2 + C_{gc}^2 + C_{ge}^2 + C_{gg}^2 + A_{wg}^2 u_{w,t-1}^2 A_{cg}^2 u_{c,t-1}^2 + A_{eg}^2 u_{e,t-1}^2 + A_{gg}^2 u_{g,t-1}^2 + 2A_{wg}A_{cg}u_{w,t-1}u_{c,t-1}$$
$$+ 2A_{wg}A_{eg}u_{w,t-1}u_{e,t-1} + 2A_{wg}A_{gg}u_{w,t-1}u_{g,t-1} + 2A_{cg}A_{eg}u_{c,t-1}u_{e,t-1} + 2A_{cg}A_{gg}u_{c,t-1}u_{g,t-1}$$
$$+ 2A_{eg}A_{gg}u_{e,t-1}u_{g,t-1} + B_{wg}^2\sigma_{w,t-1}^2 + B_{cg}^2\sigma_{c,t-1}^2 + B_{eg}^2\sigma_{e,t-1}^2 + B_{gg}^2\sigma_{g,t-1}^2 + 2B_{wg}B_{cg}\sigma_{wc,t-1}$$
$$+ 2B_{wg}B_{eg}\sigma_{we,t-1} + 2B_{wg}B_{gg}\sigma_{wg,t-1} + 2B_{cg}B_{eg}\sigma_{ce,t-1} + 2B_{cg}B_{gg}\sigma_{cg,t-1} + 2B_{eg}B_{gg}\sigma_{eg,t-1}$$

Appendix 4: Variance Equations of the BEKK Model with Dummies

$$Wheat = \left[\boldsymbol{C_{ww}} + \boldsymbol{E_{ww,1}d_{1,t}} + \boldsymbol{E_{ww,2}d_{2,t}}\right]^{2} + A_{ww}^2 u_{w,t-1}^2 + A_{cw}^2 u_{c,t-1}^2 + A_{ew}^2 u_{e,t-1}^2 + A_{gw}^2 u_{g,t-1}^2$$
$$+ 2A_{1w}A_{cw}u_{w,t-1}u_{c,t-1} + 2A_{ww}A_{ew}u_{w,t-1}u_{e,t-1} + 2A_{cw}A_{ew}u_{c,t-1}u_{e,t-1}$$
$$+ 2A_{ww}A_{gw}u_{w,t-1}u_{g,t-1} + 2A_{cw}A_{gw}u_{c,t-1}u_{g,t-1} + 2A_{ew}A_{gw}u_{e,t-1}u_{g,t-1} + B_{ww}^2\sigma_{w,t-1}^2$$
$$+ B_{cw}^2\sigma_{c,t-1}^2 + B_{ew}^2\sigma_{e,t-1}^2 + B_{gw}^2\sigma_{g,t-1}^2 + 2B_{ww}B_{cw}\sigma_{wc,t-1} + 2B_{ww}B_{ew}\sigma_{we,t-1} + 2B_{ww}B_{gw}\sigma_{wg,t-1}$$
$$+ 2B_{cw}B_{ew}\sigma_{ce,t-1} + 2B_{cw}B_{gw}\sigma_{cg,t-1} + 2B_{ew}B_{gw}\sigma_{eg,t-1}$$

$$Corn = \left[\boldsymbol{C_{cw}} + \boldsymbol{E_{cw,1}d_{1,t}} + \boldsymbol{E_{cw,2}d_{2,t}}\right]^{2} + \left[\boldsymbol{C_{cc}} + \boldsymbol{E_{cc,1}d_{1,t}} + \boldsymbol{E_{cc,2}d_{2,t}}\right]^{2} + A_{wc}^2 u_{w,t-1}^2 + A_{cc}^2 u_{c,t-1}^2 + A_{ec}^2 u_{e,t-1}^2$$
$$+ A_{gc}^2 u_{g,t-1}^2 + 2A_{wc}A_{cc}u_{w,t-1}u_{c,t-1} + 2A_{wc}A_{ec}u_{w,t-1}u_{e,t-1} + 2A_{cc}A_{ec}u_{c,t-1}u_{e,t-1}$$
$$+ 2A_{wc}A_{gc}u_{w,t-1}u_{g,t-1} + 2A_{cc}A_{gc}u_{c,t-1}u_{g,t-1} + 2A_{ec}A_{gc}u_{e,t-1}u_{g,t-1} + B_{wc}^2\sigma_{w,t-1}^2 + B_{cc}^2\sigma_{c,t-1}^2$$
$$+ B_{ec}^2\sigma_{e,t-1}^2 + B_{gc}^2\sigma_{g,t-1}^2 + 2B_{wc}B_{cc}\sigma_{wc,t-1} + 2B_{wc}B_{ec}\sigma_{we,t-1} + 2B_{wc}B_{gc}\sigma_{wg,t-1}$$
$$+ 2B_{cc}B_{ec}\sigma_{ce,t-1} + 2B_{cc}B_{gc}\sigma_{cg,t-1} + 2B_{ec}B_{gc}\sigma_{eg,t-1}$$

$$Ethanol = \left[\boldsymbol{C_{ew}} + \boldsymbol{E_{ew,1}d_{1,t}} + \boldsymbol{E_{ew,2}d_{2,t}}\right]^{2} + \left[\boldsymbol{C_{ec}} + \boldsymbol{E_{ec,1}d_{1,t}} + \boldsymbol{E_{ec,2}d_{2,t}}\right]^{2} + \left[\boldsymbol{C_{ee}} + \boldsymbol{E_{ee,1}d_{1,t}} + \boldsymbol{E_{ee,2}d_{2,t}}\right]^{2}$$
$$+ A_{we}^2 u_{w,t-1}^2 A_{ce}^2 u_{c,t-1}^2 + A_{ee}^2 u_{e,t-1}^2 + A_{ge}^2 u_{g,t-1}^2 + 2A_{we}A_{ce}u_{w,t-1}u_{c,t-1} + 2A_{we}A_{ee}u_{w,t-1}u_{e,t-1}$$
$$+ 2A_{we}A_{ge}u_{w,t-1}u_{g,t-1} + 2A_{ce}A_{ee}u_{c,t-1}u_{e,t-1} + 2A_{ce}A_{ge}u_{c,t-1}u_{g,t-1} + 2A_{ee}A_{ge}u_{e,t-1}u_{g,t-1}$$
$$+ B_{we}^2\sigma_{w,t-1}^2 + B_{ce}^2\sigma_{c,t-1}^2 + B_{ee}^2\sigma_{e,t-1}^2 + B_{ge}^2\sigma_{g,t-1}^2 + 2B_{we}B_{ce}\sigma_{wc,t-1} + 2B_{we}B_{ee}\sigma_{we,t-1}$$
$$+ 2B_{we}B_{ge}\sigma_{wg,t-1} + 2B_{ce}B_{ee}\sigma_{ce,t-1} + 2B_{ce}B_{ge}\sigma_{cg,t-1} + 2B_{ee}B_{ge}\sigma_{eg,t-1}$$

$$Gasoline = \left[\boldsymbol{C_{gw}} + \boldsymbol{E_{gw,1}d_{1,t}} + \boldsymbol{E_{gw,2}d_{2,t}}\right]^{2} + \left[\boldsymbol{C_{gc}} + \boldsymbol{E_{gc,1}d_{1,t}} + \boldsymbol{E_{gc,2}d_{2,t}}\right]^{2} + \left[\boldsymbol{C_{ge}} + \boldsymbol{E_{ge,1}d_{1,t}} + \boldsymbol{E_{ge,2}d_{2,t}}\right]^{2}$$
$$+ \left[\boldsymbol{C_{gg}} + \boldsymbol{E_{gg,1}d_{1,t}} + \boldsymbol{E_{gg,2}d_{2,t}}\right]^{2} + A_{wg}^2 u_{w,t-1}^2 A_{cg}^2 u_{c,t-1}^2 + A_{eg}^2 u_{e,t-1}^2 + A_{gg}^2 u_{g,t-1}^2$$
$$+ 2A_{wg}A_{cg}u_{w,t-1}u_{c,t-1} + 2A_{wg}A_{eg}u_{w,t-1}u_{e,t-1} + 2A_{wg}A_{gg}u_{w,t-1}u_{g,t-1} + 2A_{cg}A_{eg}u_{c,t-1}u_{e,t-1}$$
$$+ 2A_{cg}A_{gg}u_{c,t-1}u_{g,t-1} + 2A_{eg}A_{gg}u_{e,t-1}u_{g,t-1} + B_{wg}^2\sigma_{w,t-1}^2 + B_{cg}^2\sigma_{c,t-1}^2 + B_{eg}^2\sigma_{e,t-1}^2 + B_{gg}^2\sigma_{g,t-1}^2$$
$$+ 2B_{wg}B_{cg}\sigma_{wc,t-1} + 2B_{wg}B_{eg}\sigma_{we,t-1} + 2B_{wg}B_{gg}\sigma_{wg,t-1} + 2B_{cg}B_{eg}\sigma_{ce,t-1} + 2B_{cg}B_{gg}\sigma_{cg,t-1}$$
$$+ 2B_{eg}B_{gg}\sigma_{eg,t-1}$$

Appendix 5: Natural Loss of SOM Calibration

Theta (θ) is a constant decay rate of SOM. In steady state the time subscripts are dropped, and the SOM and crop residue state equations in (1) and (2) become:

$$R = R - R\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right) + H[(1-J)\alpha Y_w]\left(1 - \delta_{w,s}\right) + (1-H)[\mu Y_c]\left(1 - \delta_{c,s}\right)$$

$$S = S - \theta S + H(Y_w)\left[\alpha\delta_{w,s}(1-J) + (1+\alpha)r_w\right] + (1-H)(Y_c)\left[\mu\delta_{c,s} + \mu(1+\alpha)r_c\right] + R\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right)$$

It is assumed that wheat straw is not harvested, so $J = 0$. The crop residue and SOM state equations become:

$$R = R - R\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right) + \alpha Y_w\left(1 - \delta_{w,s}\right) + \mu Y_c\left(1 - \delta_{c,s}\right)$$

$$S = S - \theta S + Y_w\left[\alpha\delta_{w,s} + (1+\alpha)r_w\right] + Y_c\left[\mu\delta_{c,s} + (1+\mu)r_c\right] + R\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right)$$

The SOM steady state equation can be solved for the natural loss rate, θ, and the crop residue state equation can be solved for the steady state level of crop residues, R:

$$\theta = \frac{Y_w\left[\alpha\delta_{w,s} + (1+\alpha)r_w\right] + Y_c\left[\mu\delta_{c,s} + (1+\mu)r_c\right] + R\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right)}{S} \quad (a)$$

$$R = \frac{2 * \left[\alpha Y_w\left(1 - \delta_{w,s}\right) + \mu Y_c\left(1 - \delta_{c,s}\right)\right]}{\delta_{w,s} + \delta_{c,s}} \quad (b)$$

Substituting (b) into (a) yields the following:

$$\theta = \frac{Y_w\left[\alpha\delta_{w,s} + (1+\alpha)r_w\right] + Y_c\left[\mu\delta_{c,s} + (1+\mu)r_c\right] + \frac{2 * \left[\alpha Y_w\left(1 - \delta_{w,s}\right) + \mu Y_c\left(1 - \delta_{c,s}\right)\right]}{\delta_{w,s} + \delta_{c,s}}\left(\frac{\delta_{w,s} + \delta_{c,s}}{2}\right)}{S}$$

$$\theta = \frac{Y_w\left[\alpha\delta_{w,s} + (1+\alpha)r_w\right] + Y_c\left[\mu\delta_{c,s} + (1+\mu)r_c\right] + \alpha Y_w\left(1-\delta_{w,S}\right) + \mu Y_c\left(1-\delta_{c,S}\right)}{S}$$

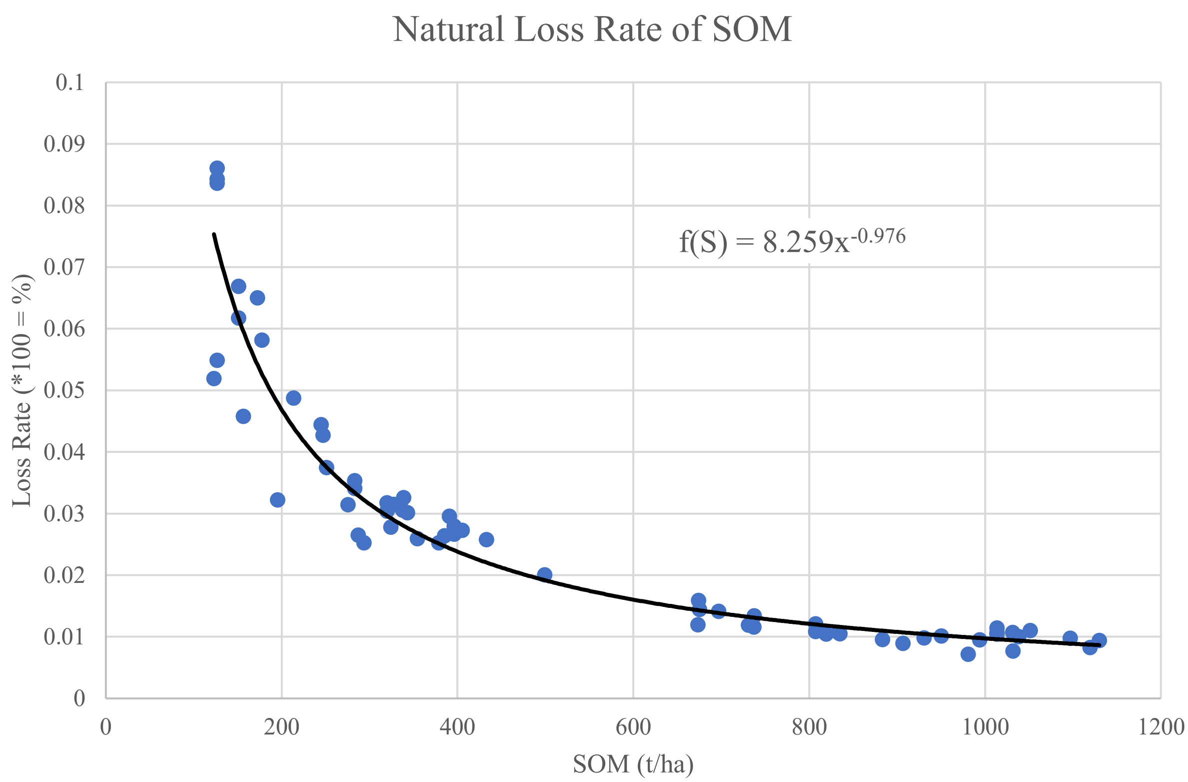
The parameter values that are presented in Table (4-1) are plugged in to get:

$$\theta = \frac{Y_w[1.3 * 0.27 + (1+1.3)0.23] + Y_c[4 * 0.32 + (1+4) * 0.32] + 1.3Y_w(1-0.27) + 4Y_c(1-0.32)}{S}$$

It is assumed that the steady state relationships of SOM and crop residues reflect an average 2 year crop rotation where wheat is grown in one year and canola is grown in the other year. Therefore, simplifying the above equation and dividing by 2 yields the following average SOM decay rate:

$$\theta = \frac{1.829Y_w + 5.96Y_c}{2S} \quad (d)$$

The natural loss rate depends on the wheat yield (Y_w), canola yield (Y_c), and the steady state level of SOM (S). The historical detrended average wheat and canola yield for each county is used in equation (d), and the steady state SOM value in equation (d) is assumed to be the SOM level reported for each county. Therefore, equation (d) is calculated for each county, and the relationship between the natural SOM loss rate and the SOM level is plotted in the figure below.


Natural Loss Rate of SOM
f(S) = 8.259x^-0.976
Loss Rate (*100 = %)
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
0
200
400
600
800
1000
1200
SOM (t/ha)

Appendix 6: Solving the Bellman Equation

Preliminaries:

1. Four grids are generated: Wheat, Wheat and Straw, Canola, and Canola with Disease. These are grids with dimensions 9 x 1,749,600 (i.e. one row for every price/surface residue/SOM/canola disease state). Columns 1-3 are the estimated low, medium, and high yields that are calculated from the yield regression equations. Mean wheat and canola yields are calculated using Equations 4.9 and 4.10, respectively.
   Columns 4-6 are the calculated surface residue stock values, based on the low/mean/high yields in columns 1-3, using Equation 4.1. Columns 7-9 are the calculated SOM stock values, based on the low/mean/high yields in columns 1-3 and the crop residues in columns 4-6, using Equation 4.6.

2. The probabilities of wheat and canola yields being low, average, or high are calculated using the *sadmvn* command from the *mnormt* package in R. The wheat and canola yield probabilities are denoted as $Q_w = (0.202, 0.596, 0.202)$ and $Q_c = (0.225, 0.550, 0.225)$, respectively.

3. Expected wheat and canola profits are calculated prior to running the DP model.
   a. Equations (4.6) and (4.7) are used to calculate expected wheat and canola profits, respectively. Expected wheat and canola profits are denoted as $E(\Pi_w)$ and $E(\Pi_c)$, respectively.

   b. Starting values of the value function, $Initial$, are chosen to be the expected canola profits.

4. Six empty 1 x 1,749,600 value function matrices are constructed: WND = Wheat No Disease, CND = Canola No Disease, WSND = Wheat and Straw No Disease, WD = Wheat Disease, CD = Canola Disease, WSD = Wheat and Straw Disease.
5. CP_x, where x = 1,2,3 or 4, is the probability of being in CDS 1,2,3 or 4.

Algorithm:

Start.

Let $j = 0,1,2,3$, where j is the canola disease state. Let $i = 1, \ldots, 729$, where i is the wheat/canola/straw price state. An index is used to reference specific rows of each grid in Step (1). The index is calculated as:

$$Index = j * \left(\frac{1,749,600}{4}\right) + 729 * i - 728$$

a) $V.Function = Initial[Index]$
b) The value function estimates for WND, CND, WSND, WD, CD, and WSD are generated by performing a bivariate linear interpolation of $V.Function$ over the SOM and crop residue state grid point values from Preliminary Step (1). Specifically, the *interp* function from the *akima* package in R is used to perform the linear interpolation.
   i. For $j = 0|2$, the value function estimates for WND, CND, and WSND are calculated, else WD, CD, and WSD are calculated.
   ii. If $j = 1|3$, the elements of WND, CND, and WSND are filled with the element values of WND, CND, and WSND when $j = 0|2$. If $j = 0|2$, the elements of WD, CD, and WSD are filled with the element values of WD, CD, and WSD when $j = 1|3$.

End.

Let $i = 1, \dots 2400$, where i is the crop residue/SOM/clubroot state. For $i = 1, \dots 2400$:

c) Each i corresponds to an interval that contains 729 observations (each price state). The interval is $[low, up]$, where:

$$up = 729 * i$$

$$low = 1 + 729 * (i - 1)$$

The calculated expected value functions are:

$$Wheat, No\ Straw = E_{low:up,1}[Z(.)] = CP_4 * WD_{low:up} + CP_3 * WND_{low:up}$$

$$Wheat\ AND\ Straw = E_{low:up,2}[Z(.)] = CP_4 * WSD_{low:up} + CP_3 * WSND_{low:up}$$

d) The optimal choice between wheat and wheat and straw is chosen and called E_w. The decision between wheat and wheat and straw depends on realized straw profits:

$$E_{low:up,w}[Z(.)] = MAX\left[E_{low:up,1}[Z(.)], E_{low:up,2}[Z(.)] + \left(p_e - g\right)\alpha Y_{w,k}\right]$$

e) The final expected value function for wheat is calculated by adding the expected profits of wheat to the product of E_w and the wheat yield probabilities matrix Q_w.

$$Z_W = E(\Pi_w)_{low:up} + \beta E_{low:up,w}[Z(.)] * Q_w$$

f) Step c) is repeated for canola:

$$E_{low:up,c}[Z(.)] = CP_1 * CCR_{low:up} + CP_2 * CNCR_{low:up}$$

g) The final expected value function for canola is then calculated by adding the expected profits of canola to the product of E_c and the canola yield probabilities matrix Q_c

$$Z_C = E(\Pi_c)_{low:up} + \beta E_{low:up,c}[Z(.)] * Q_c$$

h) The maximum between the final expected value function for canola calculated in step g) and the final expected wheat value function calculated in step e) are pulled into a new matrix where $n = 1,2, \dots 1{,}749{,}600$ called, "New". The elements of New are determined by:

$$New_n = \begin{cases} Z_{W,n}, if\ Z_{W,n} > Z_{C,n} \\ Z_{C,n}, if\ Z_{W,n} < Z_{C,n} \end{cases}$$

End

i) If Initial-New ≤ 0.5 the algorithm ends; else, New replaces Initial and the algorithm is repeated.