The role of adaptability in Western Canadian wheat variety adoption decisions

by

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Abstract

With over 300 new varieties of wheat registered in the past 15 years (Canadian Food Inspection Agency, n.d.), Canadian wheat producers have plenty of options to choose from when deciding which variety(ies) to grow. However, each year, wheat acreage in Western Canada is concentrated in a select few of these available varieties. While no single factor appears to impel this result, increasing volatility in growing conditions due to climate change is expected to significantly impact the importance of the adaptability of varieties (i.e., the ability to yield consistently under a range of conditions) in these decisions moving forward. Filling a gap in the agricultural economics literature, this research aims to empirically identify which factors drive adoption of new wheat varieties in the Canadian Prairies, focusing primarily on the role that adaptability plays in these decisions.

To do this, I first develop a conceptual framework rooted in the theory of the firm that explains the predicted relationship between varietal adaptability, measured using Torshizi's (2015) degree of specificity, and adoption. Then, using risk area level data spanning from 2009 to 2018, I empirically examine which variety attributes factor most heavily into the adoption of new wheat varieties at the prairie-wide, provincial, and wheat class levels. I also compare these results to those acquired when yield variance is alternatively used to measure varietal adaptability. In each case, I employ Pesaran and Zhou's (2018) fixed effects filter empirical approach to obtain these estimates.

Prairie-wide results reveal that more widely adopted varieties are those that have higher adaptability. These estimates also indicate that the overall success of a variety is linked to its height, protein content, fusarium head blight tolerance, and yield potential, with slight variations in results for provincial and wheat class level modeling. Further, comparison of the explanatory

power of different models points to the degree of specificity as the better measure of adaptability, relative to yield variance.

These insights into variety adoption indicate that prioritizing breeding for varietal attributes such as wider adaptability and improved yield potential may be beneficial, although balancing this with the continued need for some varieties tailored to perform under specific conditions remains important. Additionally, reporting an intuitive measure of varietal adaptability along side the other variety attribute information currently available in provincial publications would allow farmers to easily compare different varieties and ensure they are selecting the one(s) that best meet their needs. Finally, some of the challenges associated with obtaining data for this research suggest a need for more easily accessible, consistent, and representative data across Alberta, Manitoba, and Saskatchewan, to the benefit of Canadian wheat producers and industry researchers.

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Chapter 1: Introduction

1.1 Motivation

Wheat is an important element of much of the world's diet and a key agricultural product for Canada. Aggregate wheat production contributes an estimated $7 billion annually in gross farm values to Canada's economy and utilizes approximately 24 million acres (Agriculture and Agri-Food Canada & Cereals Canada, 2020). Over 90% of this production occurs in the prairie provinces of Alberta, Manitoba, and Saskatchewan (Statistics Canada, n.d.b). Outproducing domestic needs, Canada exports nearly 70% of this output to countries such as Japan, Indonesia, and Italy (Agriculture and Agri-Food Canada & Cereals Canada, 2017). As a result, Canada is one of the top five wheat exporters worldwide (United States Department of Agriculture (n.d.), with a reputation for delivering consistently high-quality wheat (Agriculture and Agri-Food Canada & Cereals Canada, 2020).

Investment in the continued development of improved wheat varieties is essential to maintaining this global market position, especially as climate conditions become increasingly volatile due to climate change. The development of new varieties with consistently higher yields and improved disease tolerance gives farmers some of the tools they need to better adapt to the changing environmental conditions they face, but it does come at a financial cost. This cost, estimated at $46 million annually in a 2015 report by JRG Consulting Group, is predominately incurred by the public sector, and supplemented by voluntary producer check-offs and private sector investments (JRG Consulting Group, 2015).

Not all new varieties are successful. Over the past 15 years, the Canadian Variety Registration Office (VRO) has registered over 300 new varieties of wheat (Canadian Food Inspection Agency, n.d.); however, adoption rates of new varieties remain significantly lower. Moreover, many registered varieties are never adopted. For example, the VRO registered 21 new varieties in 2014 (Canadian Food Inspection Agency, n.d.); but by 2019, less than half were in use by Saskatchewan wheat producers (Saskatchewan Crop Insurance Corporation, 2018). Alberta and Manitoba provide further examples of similarly low uptakes of most new varieties, as I will demonstrate in chapter four. One potential explanation for these low adoption rates is the possibility that many new varieties lack the properties Western Canadian wheat producers desire most and this in turn points to a potential disconnect in the flow of information along the Canadian wheat supply chain.

Addressing this inefficiency in Canada's wheat supply chain is crucial, especially as increasingly unpredictable growing conditions resulting from climate change add challenges for wheat producers and increase the need for the seamless flow of information between these farmers and breeders. Ensuring that producers have access to the necessary information regarding new varieties and allocating resources to breeding programs that maximize the returns on investment by producing varieties with desirable traits is important. Such actions will benefit Western Canadian wheat producers and strengthen Canada's international market position. The first step towards this is developing a clearer understanding of wheat producer variety decisions in the Canadian Prairies through identifying the key factors in these choices.

Existing literature has sought to identify some of these factors. Barkley and Porter's (1996) study of Kansas wheat producer variety decisions points to end-use values and expected yields as key variety traits. Comparing North Dakotan producers with those in the Canadian Prairies, Dahl et al. (1999) find that agronomic traits carry relatively more weight than end-use values north of the border. However, neither of these studies consider the influence of the adaptability of a variety in adoption decisions. Referring to varieties that perform consistently well under a greater range of environmental conditions, more adaptable varieties can reduce the risks to farmers that stem from increasing climate volatility due to the effects of climate change. To the best of my knowledge, none of the economic literature on Canada's wheat variety adoption factors considers the influence of this trait in these decisions. Further, the general approach to modeling crop variety adoption decisions relies on pooled data approaches due to the time invariant nature of several varietal traits and associated limitations of panel data empirical models. No studies account for the effects of both time invariant variables and the differentiated nature of varieties within this context.

This thesis provides two key contributions to the literature on crop adoption. First, it explicitly explores the role of adaptability on wheat variety adoption in Canada. Second, it applies Pesaran and Zhou's (2018) fixed effects filter (FEF) panel data approach in the context of wheat varietal decisions, which has advantages over more commonly used methods such as the pooled ordinary least squares (pooled OLS), fixed effects, and Hausman-Taylor instrumental variable (Hausman-Taylor IV) approaches. Such advantages include accounting for the panel nature of the data, while allowing for the estimation of time invariant trait effects which the standard fixed effects approach cannot handle. This is important for the literature on the economics of innovation in general, and for the case of innovation adoption modelling in particular, where dealing with both time variant and invariant factors is common.

Insights gained from this research may be beneficial to various wheat industry stakeholders. For breeders, the empirical results of this study provide a closer look at the importance of several varietal attributes to Canadian wheat producers. Further, several of the variety characteristics that I examine are identified by Agriculture and Agri-Food Canada and Cereals Canada (2020) as key wheat research priorities. These include improvements in yield potential, disease tolerances, and adaptability. By empirically examining the relationship between these variety characteristics and adoption, I provide additional insights that may further inform such initiatives. Finally, by using the varietal information available to Canadian wheat producers, I am able to provide some insights into some of the challenges associated with accessing consistent and representative information on the wheat varieties available across Western Canada.

1.2 Objective

The main objective of this thesis is to empirically examine the factors (i.e., seed traits such as disease tolerance, protein content, yield potential, etc.) that drive the adoption of new wheat varieties in the Canadian Prairies. Wheat is grown in several Canadian provinces, however, Alberta, Manitoba, and Saskatchewan account for approximately 93% of planted acres (Statistics Canada, n.d.b). For this reason, I concentrate on identifying what makes some varieties more successful than others in these three provinces. Data used in this research comes from the Canadian Food Inspection Agency (CFIA) [1] and from provincial Seed Guides[2] and Yield

[1] Canadian Food Inspection Agency (n.d.)

[2] Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.), Saskatchewan Seed Growers' Association (n.d.)

Magazines[3], which provide information on characteristics such as yield, maturity rates, and disease resistance factors. In particular, I focus on identifying the relationship between the adaptability of new wheat varieties and their adoption rates.

1.3 Empirical approach

To establish the expected relationship between a variety's adaptability and its adoption, I develop a framework rooted in the theory of the firm and based primarily on the approach of Torshizi (2015). Under this framework, farmers select varieties with the varietal traits that they believe will perform best in the growing conditions they face, thereby maximizing their expected producer surplus. Assuming that more adaptable varieties reduce the risks and uncertainty around realized yields, this framework indicates adoption should increase with varietal adaptability.

Addressing the research question empirically, I use a FEF regression approach to estimate adoption rates of various wheat varieties as a function of varietal traits at three levels: prairie-wide, provincial, and wheat class. This approach follows that of Dahl et al. (1999), but accounts for the intrinsically differentiated nature of wheat varieties. Further, it provides an applied example of Pesaran and Zhou's (2018) modified fixed effects model within the context of crop variety adoption decisions.

Longitudinal (or panel) data on the insured acreage of each variety forms the dependent variables, while numerous varietal traits (e.g., yield potential, adaptability, and other agronomic and quality characteristics) form the set of explanatory variables. The model also allows for a hill-shaped lifecycle that characterizes variety adoption. This dataset covers the period 2009 to 2018 for Alberta, Manitoba, and Saskatchewan, the major wheat producing provinces. Variety characteristics come from the respective provincial Seed Guides and yield data from the Yield Magazines.

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[3] Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.), Saskatchewan Crop Insurance Corporation (n.d.)

1.4 Organization of the study

Chapter two provides an overview of the Canadian wheat supply chain, followed by a review of the relevant literature. The background portion of this chapter is a discussion the key elements of each point on the supply chain, from initial research to final consumers and the monitoring role of the Canadian Grain Commission. Following this, the literature review portion begins by summarizing previous findings on agricultural technology adoption, narrowing in focus to general determinants for technology, and more specifically crop variety adoption. Finally, chapter two discusses the existing literature on wheat variety decisions in particular and concludes with a look at previous studies that consider the importance of variety adaptability.

Chapter three presents the conceptual framework of this thesis. As previously discussed in section 1.4, this framework uses a producer surplus maximization approach to explain the relationship between variety adaptability and adoption levels. I use the results from my conceptual model to guide my empirical modeling of variety adoption and form testable hypotheses in chapter five.

Chapter four, provides a summary of the dataset collection and construction process. I begin this chapter by discussing the construction of provincial datasets, and the process to aggregate these into a prairie-wide dataset. Following this, I discuss the distribution of acres across varieties, based on observations from this dataset. This chapter concludes by elaborating on some of the challenges of the data collection process and provides an overview of the representativeness of the dataset.

Chapter five outlines the empirical approach. I begin with a brief overview of some of the empirical approaches used in the existing literature, followed by an outline of the research aims. Next, I provide a discussion of the advantages and disadvantages of various relevant empirical approaches available, concluding that Pesaran and Zhou's (2018) FEF approach is the most appropriate. Following this, I provide the dependent and independent variables used in modeling adoption, as well as summary statistics for each. The chapter concludes with the presentation of the econometric models and a discussion of the estimation procedures.

Chapter six presents the empirical estimates for variety adoption. I begin by noting some of the empirical considerations contributing to the selection of results presented. Estimated results for the prairie-wide level follow next, with subsequent sections on provincial and wheat class level results. Next, I summarize the main findings and implications of the empirical estimates, followed by a discussion of possible explanations for unexpected estimated signs for some varietal trait coefficients. Finally, the chapter concludes with a few notes on some of the limitations of these results.

Chapter seven summarizes the thesis and its findings. It includes the conclusions and insights drawn from these results. Additionally, chapter seven revisits some of the limitations of this study and provides suggestions for further research.

Chapter 2: Background and literature review

2.1 Introduction

This chapter is divided into two main sections: a background of the Canadian wheat supply chain and a review of the relevant literature. The first section breaks down the key stages of wheat production in Canada, from research and breeding to final consumption and end uses. The second section considers the literature in agricultural technology adoption, with focuses on wheat variety adoption factors and more specifically, the importance of a variety's adaptability.

2.2 Background of the Canadian wheat supply chain

This section outlines the Canadian wheat supply chain. This complex chain is comprised of several steps, from initial research, to final consumption with various institutions taking on important roles at each stage. Each step and the flow of information between them play crucial roles in the Canadian wheat industry. Therefore, it is important to understand the mechanics of the whole supply chain in order to examine the flow of information within it. Organized into eight sections (Figure 2.1), this overview looks at who the big players in the wheat industry are and what happens at each point on the supply chain.

Figure 2.1 Canadian wheat supply chain

Given the scope of this thesis, my primary focus is on farmers in the fourth element. Developing a better understanding of this point on the supply chain generates insights that may be relayed to earlier stages to ensure these stages are meeting the needs of those farther down the supply chain. Further, given the interconnected nature of Canada's wheat industry, farmers variety decisions reflect their perceptions of end user desires. Therefore, these insights from one particular point in the supply chain contribute to the overall understanding of wheat production in Canada.

2.2.1 Research and breeding in Canada

Several institutions conduct research on wheat variety improvement in Canada. Much of this research is conducted by public institutions, however, some private companies contribute to new wheat varieties. Table 2.1 provides a list of 2019 breeders, obtained from provincial Seed Guides.

Table 2.1: Wheat breeders in Canada (2019)

Sector	Breeders	Wheat Classes
Public	Agriculture and Agri-Food Canada	CWRS; CWSP; CWAD; CPSR; CNHR*; CWHWS; CWSWS; CWRW; CWEW
	Field Crop Development Centre	CWSPW
	North Dakota State University	CWRS; CNHR
	University of Alberta	CWRS
	University of Saskatchewan – Crop Development Centre	CWRS; CWSP; CWAD; CPSR; CNHR; CWHWS; CWRW; CWSPW
Private	KWS – UK	CWSP
	Syngenta Seeds Canada Inc.	CWRS; CWSP; CNHR*; CPSR
	Wiersum Plant Breeding	CWSP

Sources: Saskatchewan Seed Growers' Association (2019), Alberta Seed Growers & Alberta Seed Processors (2019)

**Some CWRS are in the process of being moved to CNHR (select AAFC and Syngenta CWRS varieties)*

Class key: Canada Western Red Spring (CWRS); Canada Western Special Purpose (CWSP); Canada Western Amber Durum (CWAD); Canada Prairie Spring Red (CPSR); Canada Northern Hard Red (CNHR); Canada Western Hard White Spring (CWHWS); Canada Western Red Winter (CWRW); Canada Western Special Purpose Winter (CWSPW); Canada Western Soft White Spring (CWSWS); Canada Western Experimental Winter (CWEW)

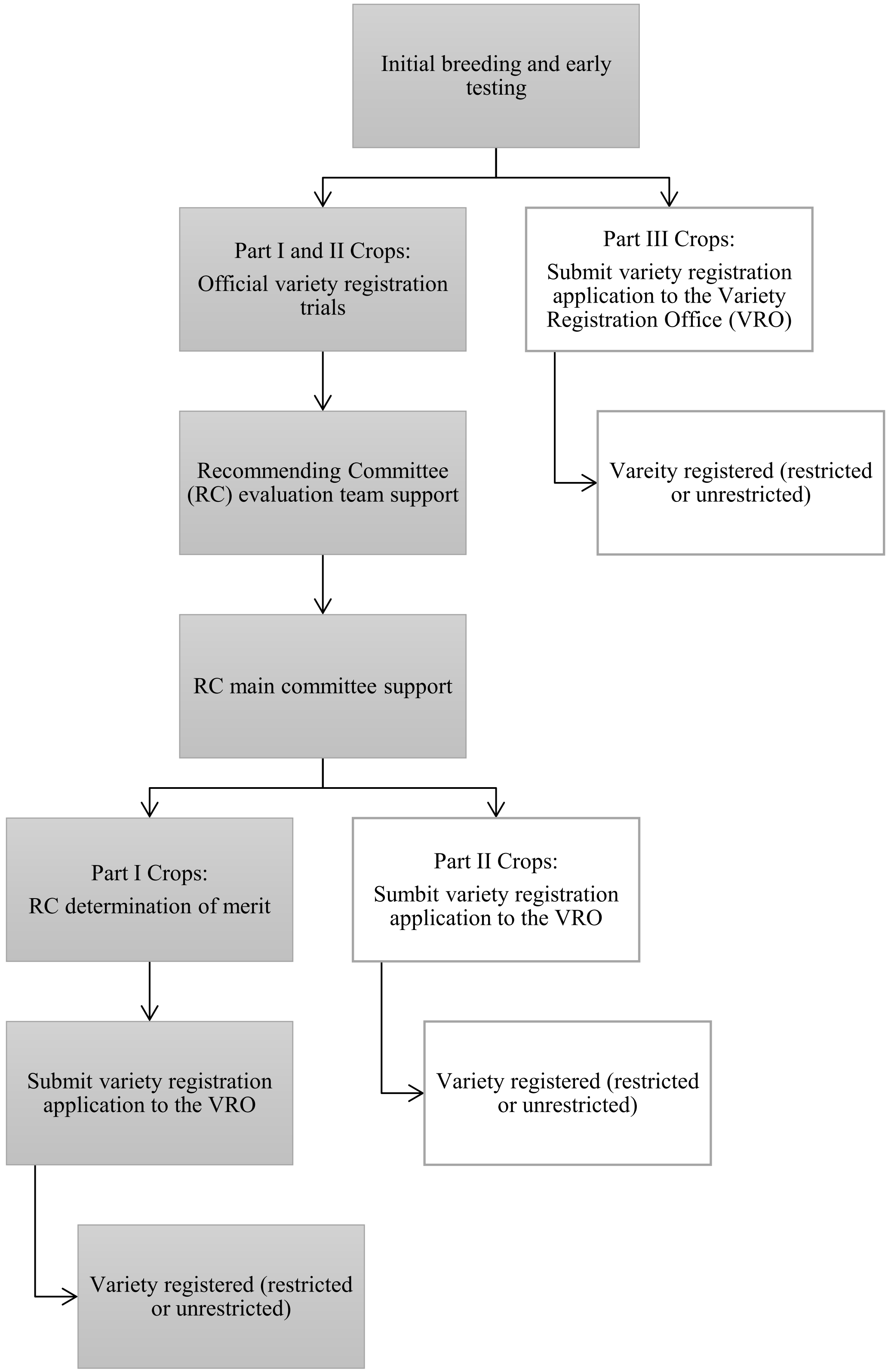
A combination of public and private investments fund research on new wheat varieties, with total Canadian expenditures on wheat varietal development estimated at $46 million per year (JRG Consulting Group, 2015). Approximately 73% of this investment comes from public sources, with the remaining 26% split evenly between producer and private sources (JRG Consulting Group, 2015). Some examples of public sources include the Canadian Wheat Alliance's $97 million five-year commitment and the National Wheat Improvement Program's $25 million investment (JRG Consulting Group, 2015). Voluntary producer check-offs, administered by the relevant provincial wheat commission upon delivery of grain to a licensed elevator, serve as a major source of producer contributions to industry research, development, and technical support (Quorum Corporation, 2019). The Western Grains Research Foundation (WGRF) collects these check-offs and then invests them back into the industry (Froystad, 2012). With a Western Canadian Deduction levy of $0.48 per tonne, the 2018 WGRF's Wheat Fund balanced at nearly $29 million (Western Grains Research Foundation, 2019). Limited private sector research and investments occur, however, competition from farm-saved seed limits breeder's abilities to capture majority shares of the surplus gains from innovation, reducing the attractiveness of private sector investments into the advancement of Canadian wheat varieties (JRG Consulting Group, 2015).

2.2.2 Variety registration process

Variety registration (VR) aims to ensure the delivery of desired end-use qualities to buyers and pertains to most major Canadian crops, including wheat (Agriculture and Agri-Food Canada, 2013a). Development and registration of new wheat varieties in Canada often takes upwards of 12 years, from initial breeding to the marketing of seed (see Figure 2.2) (Agriculture and Agri-Food Canada, 2013a; Agriculture and Agri-Food Canada 2013b). I outline this registration process, administered by the Variety Registration Office (VRO) of the Canadian Food Inspection Agency (CFIA), in Figure 2.2 (Agriculture and Agri-Food Canada, 2013a). According to the CFIA (2012), to be eligible for registration, wheat varieties must:

- Not be detrimental to humans, animals, and the environment,
- Meet the Canadian Seed Growers Association's varietal purity standards,
- Be distinguishable from all other registered varieties,
- Meet name regulations (e.g., not offensive or misleading), and
- Have sufficient and accurate information to be evaluated.

Figure 2.2: Canadian variety registration process



Source: Agriculture and Agri-Food Canada (2013b)

To allow some flexibility for different crops, the VR system divides seeds into three tiers, with wheat designated a Part I crop (Agriculture and Agri-Food Canada, 2013b). All tiers undergo an initial breeding and early testing stage (Agriculture and Agri-Food Canada, 2013b). For wheat, this stage generally entails a minimum of six years (Agriculture and Agri-Food Canada, 2013b). Following this, proposed wheat varieties enter into official trials under the supervision of a recommending committee (RC) (Agriculture and Agri-Food Canada, 2013b). In Western Canada, this is the Prairie Recommending Committee for Wheat, Rye and Triticale (PRCWRT) (Agriculture and Agri-Food Canada, 2013b). To obtain support from the PRCWRT, agronomy, disease, and quality teams within the PRCWRT evaluate three years of trial results for the proposed variety (Agriculture and Agri-Food Canada, 2013b). Receiving the approval of these teams, the main committee then votes on granting or withholding support for the new variety (Agriculture and Agri-Food Canada, 2013b). For the PRCWRT, this main committee vote typically occurs in February of each year (Prairie Grain Development Committee, 2019).

In addition to these steps, Part I crops must also receive a designation of having merit by the RC (Agriculture and Agri-Food Canada, 2013b). To be granted this designation, the new wheat variety must demonstrate equal or superior performance to specific characteristics of the reference variety (Agriculture and Agri-Food Canada, 2013b). These minimum standards are crop specific and set by the RC, with a focus on relative overall performance (Agriculture and Agri-Food Canada, 2013b).

The final requirement of the VR application is the basic registration package, submitted by all tiers to the VRO (Agriculture and Agri-Food Canada, 2013b). This package requires several pieces of information, including:

- Scientific, proposed, and common variety names,
- Pedigree, history, and development methods,
- A detailed description of characteristics,
- Information about novel traits, if applicable,
- Specific to wheat, a statement of eligibility from the Canadian Grain Commission (CGC),
- Appropriate fees.

Once all requirements are met, a completed application is submitted to the VRO. After reviewing and verifying the application, the VRO registers the new wheat variety. There are four possible registration statuses (Canadian Food Inspection Agency, 2012):

(1) Unrestricted registration: no restrictions, valid across Canada unless otherwise stated
(2) Regional registration: restricted to certain regions due to the potential adverse effects if grown in other regions
(3) Interim registration: full rights (regional or national) for a specified period of time (maximum life of 5 years)
   - This status is granted either for conducting market acceptability tests or for emergency reasons.
(4) Contract registration: due to biochemical or biophysical traits, quality control systems and isolation distances are potentially required to protect the traditional variety
   - For wheat and barley, the CGC and VRO co-determine the acceptability of a quality control system.

The VRO's review process standard is 8 weeks for processing an application (Agriculture and Agri-Food Canada, 2013b). Once approved by the VRO, the applicant receives a certificate of registration and the variety appears on the CFIA's list of registered varieties (Canadian Food Inspection Agency, 2012).

2.2.3 Western Canadian seed distributors

The third step of Canada's wheat supply chain is seed distribution. Canadian seed distributors facilitate the purchase of CFIA certified seeds by farmers (Canadian Seed Growers' Association, 2020). By providing these distribution channels, seed distributors give Canadian farmers access to high quality seeds with strong genetic potential (FP Genetics, n.d.). Table 2.2 provides a list of these distributors for wheat seeds in Canada.

Table 2.2: Wheat seed distributors in Western Canada (2019)

Distributors
Alliance Seed
Canterra Seeds
Cargill
Faurschou Farms Ltd. III
FP Genetics
Lefsrud Seed
Mastin Seeds
Nutrien Ag Solutions
Proven Seed
Public release University of Saskatchewan – Crop Development Centre
Richardson International
SeCan Members
Seed Depot
SeedNet Inc.
Syngenta Canada
United Suppliers Canada
Western Ag
Western Feed Grains Development Co-op Ltd.

Sources: Alberta Seed Growers, & Alberta Seed Processors (2019), Saskatchewan Seed Growers' Association (2019) and Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (2019)

2.2.4 Farmers and production statistics

Canadian wheat farmers are the next key players in the supply chain. According to the 2016 census, Canada allocates approximately 23 million acres to wheat production each year (Statistics Canada, n.d.b). Based on the roughly 52,500 reporting farms, the average wheat farm in Canada is about 450 acres (Statistics Canada, n.d.b). Table 2.3 provides a provincial breakdown of the number of farms in the prairie provinces.

Table 2.3: The number of Canadian wheat farms and average farm size by prairie province (2016)

Province	Number of farms	Acres	Average wheat acreage	Share of total acres
Alberta	11,634	7,008,542	602	29.9%
Manitoba	5,913	2,997,013	507	12.8%
Saskatchewan	17,650	11,840,688	671	50.5%
Canada	52,497	23,436,513	446	

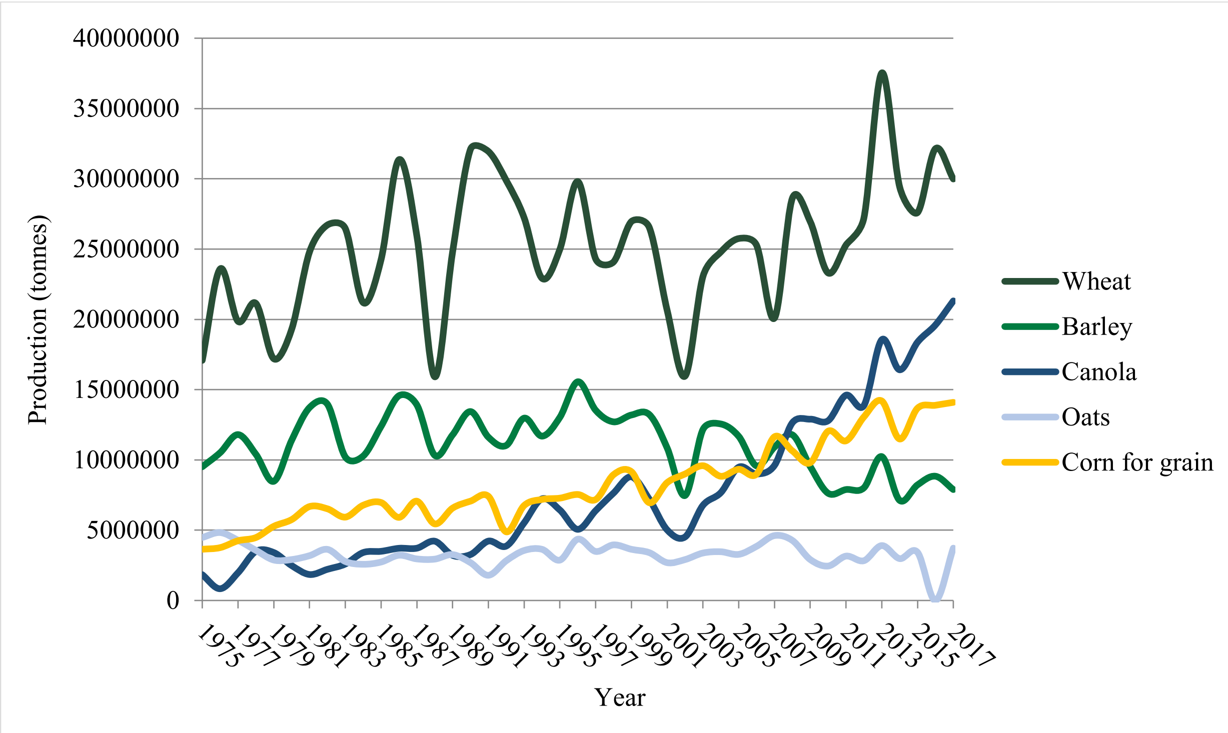
Source: Statistics Canada (n.d.b)

Planting decisions are believed to centre around net financial returns per acre (Quorum Corporation, 2014b). Farmers consider their own technical expertise, land and climate conditions, and a balance of financial returns with acceptable costs and risks (Quorum Corporation, 2014b).

One element of this decision process is crop rotation. Most Canadian wheat farmers rotate their crops, which means that they change the crop planted in a field each crop year in order to provide optimal growing conditions and to respond to changing commodity prices (Government of Saskatchewan, 2017). In the case of wheat, the Government of Saskatchewan (2017) recommends using different cereals each year, and planting a non-cereal, such as oilseed, pulse, or legume crops, every third year. These rotations serve to manage water use, nutrient levels, and disease tolerance (Government of Saskatchewan, 2017).

Wheat production levels dominated overall grain production in Canada between 1975 and 2017 (Figure 2.3). Over this period, production of wheat trended upwards, though the gap between wheat and canola production diminished. Breaking Canadian wheat production down into its different varieties and grouping them into spring, durum, and winter varieties for the 2017-2018 crop year, Table 2.4 reveals that spring wheat varieties compose the largest share of production for that season.

Figure 2.3: Canadian key crop production (1975-2017)



Source: Statistics Canada (n.d.a)

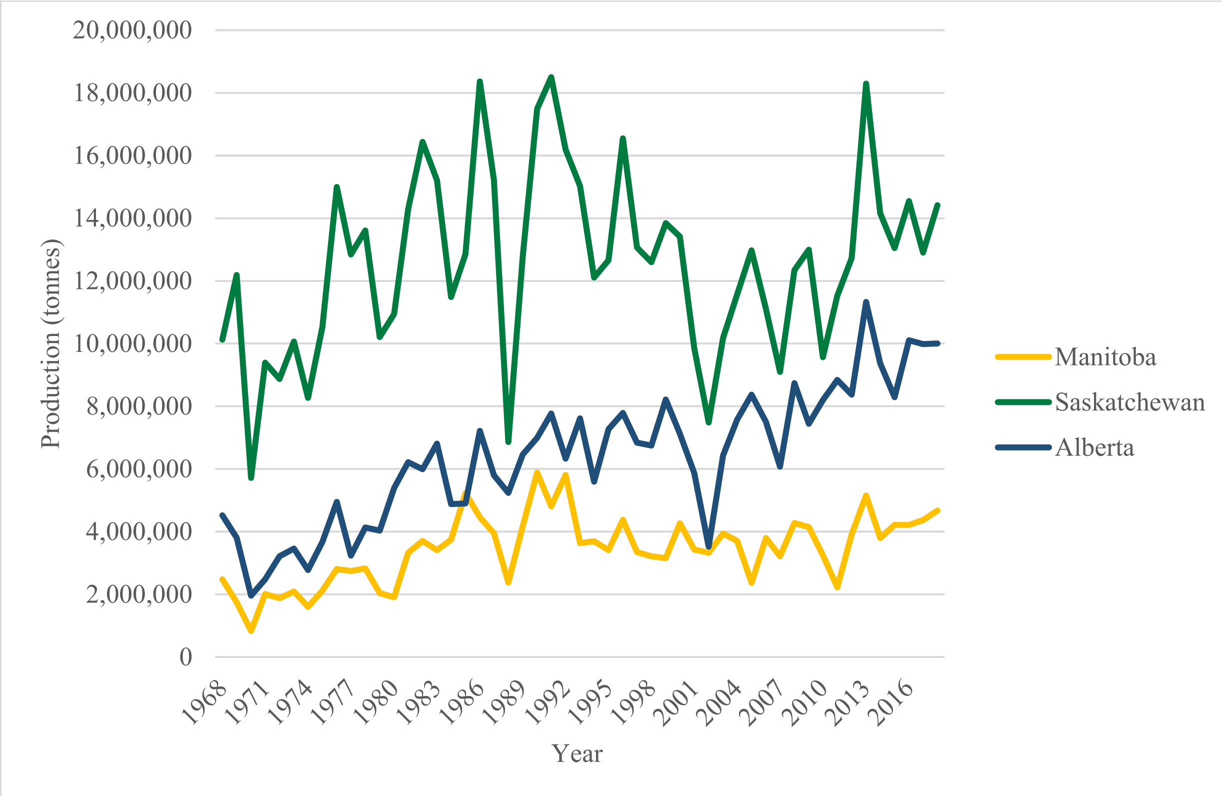
Table 2.4: Canadian wheat production (2017-2018 crop year)

Wheat Class	Production (tonnes)	Share of Production
Durum	4,977,000	15.4%
Spring	25,670,400	79.4%
Winter	1,700,500	5.3%
Total	32,347,900	

Source: Statistics Canada (n.d.a)

Geographically, wheat is primarily grown in Western Canada. According to the 2016 Statistics Canada census, the three prairie provinces account for approximately 93% of total wheat acres (Statistics Canada, n.d.b). British Columbia, Ontario, and Quebec also grow wheat, however these provinces account for a significantly smaller portion of total Canadian acres. Focusing on the Canadian Prairies, Saskatchewan historically leads the way in wheat production (Figure 2.4).

Figure 2.4: Wheat production in the Canadian prairie provinces (1968-2018)



Source: Statistics Canada (n.d.a)

Unlike other countries, Canadian farmers generally sell to grain companies, who manage future movements to final consumers (Slade & Gray, 2018). This means that Canadian grain farmers do not always directly interact with further downstream supply chain participants. Some farmers may directly manage the sale of spoiled grain for animal feed, but grain headed for international markets is generally sold by grain companies (Quorum Corporation, 2014b). However, as costs flowing back upstream affect the price of grain that farmers receive, their decisions still depend on these downstream grain markets (Slade & Gray, 2018).

2.2.5 Grain companies

Grain companies purchase grain from producers to sell in domestic and international markets. There are several grain companies in Canada, with six of the largest being:

- Viterra,
- Richardson International,
- Cargill Canada,
- Parrish and Heimbecker,
- Louis Dreyfus, and
- Paterson Global Foods.

In 2014, these six grain companies owned 246 of 391 licensed primary and process elevators, with 75% of the 6.85 million metric tonnes of total storage capacity for grain (Quorum Corporation, 2014b). Another 76 grain companies ran the remaining 145 elevators. Of the 29 Canadian port terminal facilities, grain companies operated 25 (Quorum Corporation, 2014b). An updated list includes G3 and Bunge (Torshizi & Gray, 2017), with most primary elevators in Canada owned by one of these eight grain companies. In addition, these eight own all export facilities at the ports of Metro Vancouver, Prince Rupert, and Thunder Bay (Torshizi & Gray, 2017).

In the US, grain companies and farmers use forward contracts or cash purchases (Quorum Corporation, 2014a). This system mitigates some of the risk to producers (Quorum Corporation, 2014a). As of 2014, forward contracts are uncommon in Canada, in part due to the Canadian wheat industry's historic use of a single desk system (Quorum Corporation, 2014a). However, with the end of the Canadian Wheat Board (CWB), the use of contracts in grain markets is expected to increase (Quorum Corporation, 2014a).

2.2.6 Transportation to export positions and domestic markets

Canadian grain headed for international markets is exported mainly via rail to port movement, with some direct rail or road export. As, according to Quorum Corporation (2014b), grain travels an average of 1500 kilometres from elevator to port, 95% of this grain movement occurs on Canadian National and Canadian Pacific railways. Eighteen short line rails supplement these longer tracks (Quorum Corporation, 2014b). Due to this reliance on the Canadian rail system, factors such as car supply significantly impact the movement of grain to export markets. However, progress has been made on increasing the number of hopper cars available for grain shipments (Quorum Corporation, 2020). This effort contributed to a decline of 4.4% in average days to move grain through the Grain Handling and Transportation system to 43.8 days in the 2018-2019 crop year (Quorum Corporation, 2020).

Canadian freight rate policy has changed over the past 30 years, beginning as the Crow Rate and evolving to the Maximum Revenue Entitlement (MRE) program (Quorum Corporation, 2014b). The MRE acts as an inflationary control mechanism, where increases in rate should reflect higher underlying costs (Quorum Corporation, 2014b).

Ports also influence the movement of grain, as rail cars must be emptied in a timely fashion in order to avoid rail system delays. The four wheat export ports are Vancouver, Prince Rupert, Thunder Bay, and Churchill, though access to the port of Churchill was blocked for nearly four years due to necessary rail repairs, with shipments resuming by the end of 2018 (Quorum Corporation, 2020). At the other ports, the 2018-2019 crop year saw a decline in storage time at terminal elevators which aided in reducing overall transportation time (Quorum Corporation, 2020).

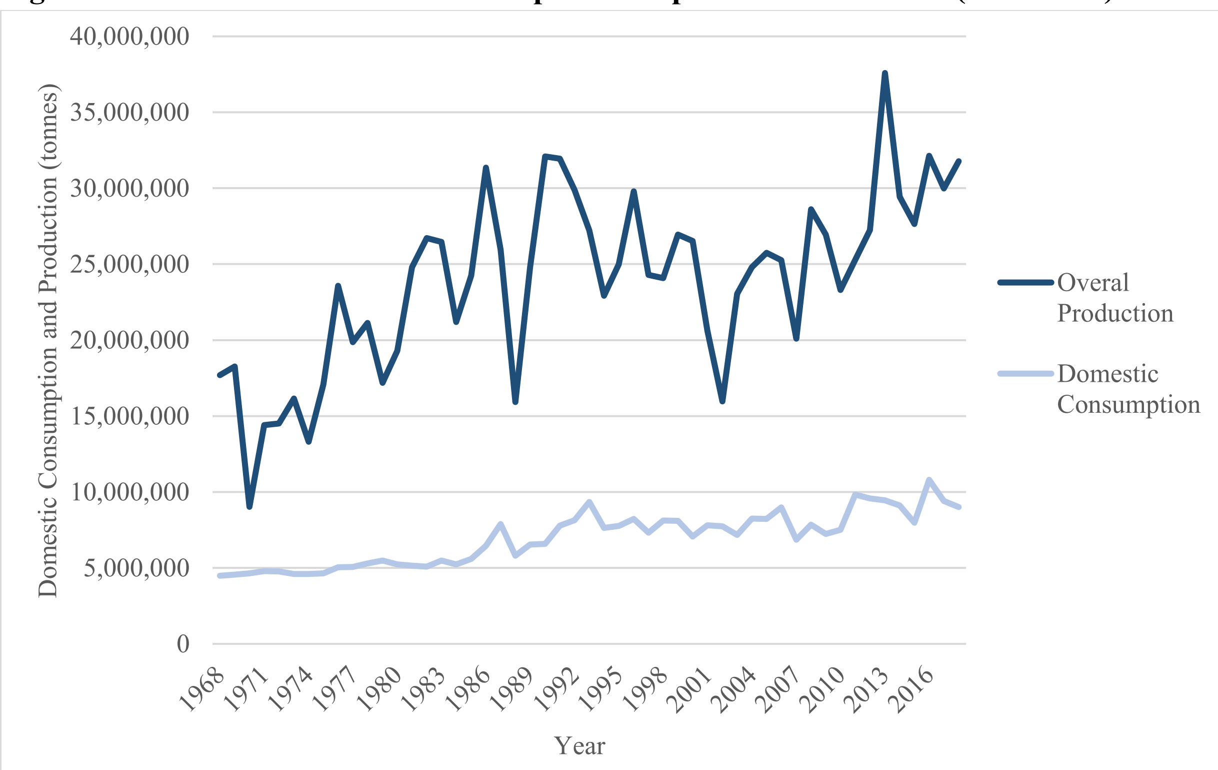
Movement of grain to domestic consumers differs by the intended use. Feed grain is generally sold locally, with little significant influence on the grain supply chain (Quorum Corporation, 2014c). However, non-local movement of grain for milling use parallels that of export sales. Grain companies purchase product from farmers, and transport it via rail and roads to domestic millers responsible for processing and selling the resulting product to consumers (Quorum Corporation, 2014c).

2.2.7 Final consumers and end uses

Canadian wheat has a variety of end uses. The largest production class, CWRS, is used for bread, noodles, and pasta while durum wheat is a key input in pasta and couscous production (Canadian Grain Commission, 2019b). Other varieties are used in various types of breads, noodles, cookies, cakes, and pastries (Canadian Grain Commission, 2019b). However, CWSP wheats are generally limited to use in biofuels or for animal feed due to their starch and protein contents (Canadian Grain Commission, 2019b).

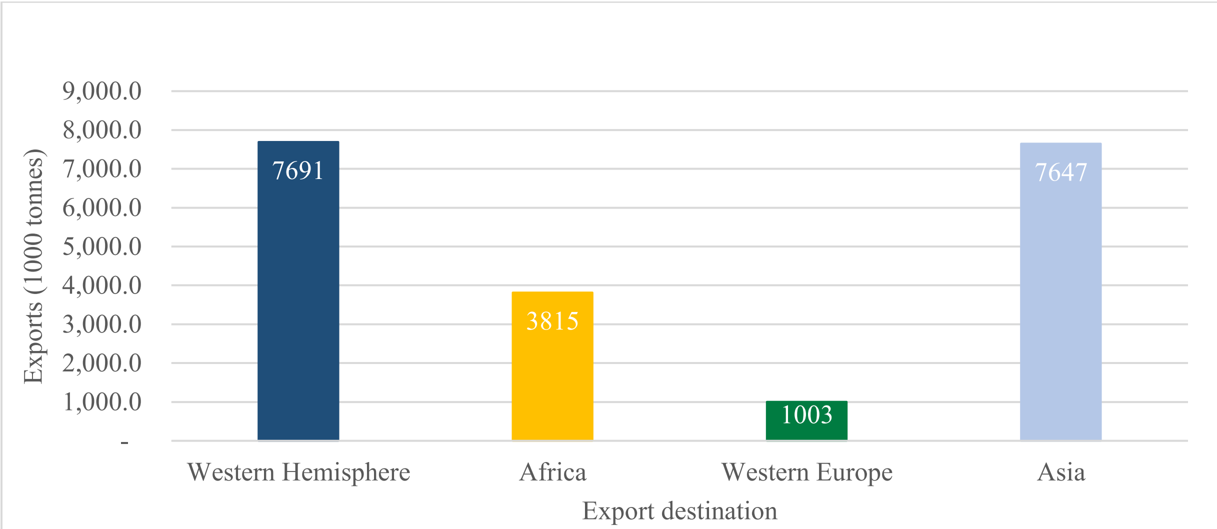
Annual domestic consumption of wheat increased overall since 1968, however, it is well below annual production levels (Figure 2.5). As a result, Canada exports the majority of its wheat production. For the 2017-2018 crop year, the top three destinations of Canadian wheat were Indonesia, the United States, and Japan, each importing over 1.5 million metric tonnes (Canadian Grain Commission, 2019a). Western Europe accounts for a small portion of Canadian wheat exports, with roughly 75% of exports going either to other nations in the Western Hemisphere or to Asia (Figure 2.6) (Canadian Grain Commission, 2019a). With its large surplus, Canada generally ranks in the top five globally in wheat exports (Figure 2.7).

Figure 2.5: Canadian domestic consumption and production of wheat (1968-2018)



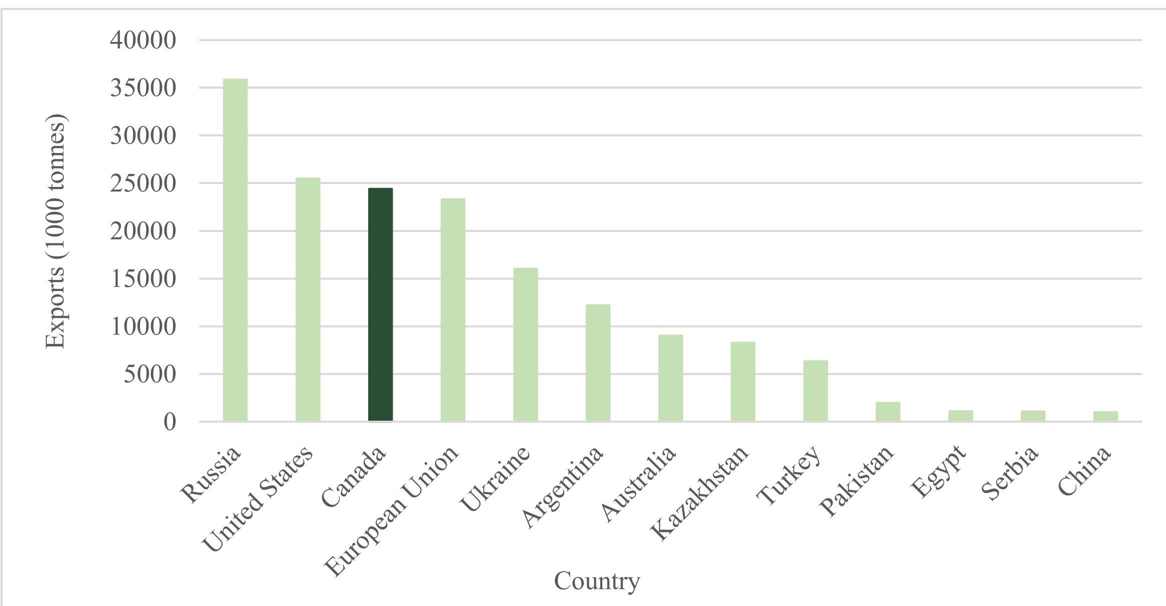
Source: Statistics Canada (n.d.a) and Index Mundi (n.d.)

Figure 2.6: Canadian wheat export destinations (2017-2018 crop year)



Source: Canadian Grain Commission (2019a)

Figure 2.7: Wheat export rankings for select countries (2019)



Source: United States Department of Agriculture (n.d.)

2.2.8 Canadian Grain Commission monitoring

As the official regulator, the CGC's primary purpose is to ensure consistent quality of Canadian grain (Canadian Grain Commission, 2019c). Overseen by the Ministry of Agriculture and Agri-

Food, the CGC runs quality, research, and safeguard programs with the aim of protecting Canada's reputation for dependable and safe grain in both domestic and international markets (Canadian Grain Commission, 2019c). Further, the CGC provides the official grain grading scale, used to determine what grade outputs can be marketed as (Canadian Grain Commission, 2019c). For wheat, these grades are applied within wheat classes and establish three to five quality levels for marketing, depending on the class (Canadian Grain Commission, 2018). If a variety is not registered in Canada, it can only be sold under the lowest grade for its wheat class (Canadian Grain Commission, 2018). Other roles of the CGC include ensuring farmers receive appropriate compensation for their grain (Canadian Grain Commission, 2019c), and administering producer railcar orders (Quorum Corporation, 2014b).

2.2.9 Wheat prices and seed costs

Canadian wheat producers receive a cash bid price from grain companies equal to the free on board (FOB) port price, less an export basis reflecting grain handling and transportation costs for their output (Torshizi & Gray, 2017; Slade & Gray 2018). As Canada is a small player in the world wheat market, the FOB price may be considered exogenous to domestic supply (Slade & Gray, 2018). According to Slade & Gray (2018), the combination of exogenous FOB prices and MRE restricted freight prices means that domestic supply shocks are largely absorbed by producers. While it is plausible that the CWB dampened the effects of these domestic supply shocks in the past, in its absence farmers feel the full effects of these price changes (Slade & Gray, 2018).

Seed costs to Western Canadian wheat farmers are relatively low, reflecting reproduction and bagging costs, and come in two forms. The first are direct seed and treatment costs, estimated at $29.00 per acre for hard red spring wheat in Manitoba for 2021, which is substantially lower than seeding and treatment costs for many other grains and oilseeds (e.g., canola runs a $67.50 bill per acre seeded) (Government of Manitoba, 2021). This difference in seeding costs is likely in part due to wheat's largely public and producer investment driven variety development market, which minimizes private seed companies' market power. The second cost is the voluntary collection of check-offs upon delivery to a grain elevator that are then invested back into the industry (Froystad, 2012). For 2018, this levy was set at $0.48 per tonne (Western Grains Research Foundation, 2019).

However, the percentage of wheat producers who purchase certified seed each year is relatively low. This is because Canada allows wheat producers to save and clean seed from their own production for future use, though trade or sale of these saved seeds is prohibited (Government of Alberta, 2018). Due to perceived lower costs and relatively equivalent quality, combined with the security in "knowing what they are getting", reports indicate that roughly 70% of producers choose farm saved seed over purchasing certified seed each year (Government of Alberta, 2018). According to the Government of Alberta (2018), the costs to producers of this practice largely reflect the foregone revenue of the grain saved for seeding the next year and associated cleaning costs.

2.3 Literature review

This section reviews the relevant literature on agricultural technology and, more specifically, crop variety adoption. It begins with a summary of the literature on agricultural technology adoption. This summary outlines the process of adoption, diffusion, and the uncertainty associated with agricultural technology. Next, I discuss the general characteristics of agricultural technology that contribute to its adoption. Following this, I focus on the factors of crop variety adoption and then more specifically, wheat variety adoption. The last section examines the literature on the role of adaptability in decisions regarding adoption of varieties.

2.3.1 Adoption, diffusion, and uncertainty in agricultural technology adoption

As new technology is introduced, the process by which farmers choose to adopt or not provides key insights into which factors contribute to the successful adoption of these innovations. Extensive literature on this adoption process places emphasis on the factors that affect it and the learning process that reduces uncertainty, starting from the seminal works of Griliches (1957) and Rogers (1962).

The diffusion process reflects the lag observed between the time that new technology is introduced and the time that the average producer decides to adopt it. This delay stems from the initial uncertainty surrounding the performance and benefits of a new agricultural technology for individual producers due to differences in other factors of production, such as farmer experience, regional weather patterns, and soil quality (Pannell et al., 2006). Pannell et al. (2006) break this adoption process for individual producers into six stages: awareness, non-trial evaluation, trial evaluation, adoption, revision, and disadoption. In the first stage, producers are aware that a new technology is available and that it may be beneficial to them. Once aware of the innovation, farmers collect information on its viability and gauge whether or not it is worthwhile to move onto the trial stage. For divisible technology like crop varieties, the likelihood of adoption falls significantly if the technology is not conducive to small-scale trialling. Where small-scale trials are successful, or farmers are able to obtain adequate information via alternative sources, the technology moves on to the adoption stage where its use increases. For many agricultural technologies, including new crop varieties, partial adoption is possible. This means that farmers decide whether or not to adopt, as well as the intensity of adoption. However, adoption is a continuous process, and farmers revise their decisions regarding the technology as new information becomes available over time. This creates a possible shift towards disadoption in later stages, as circumstances change and older technology is phased out in favour of updated production techniques or improved varieties (Dinar & Yaron, 1992; Fernandez-Cornejo & McBride, 2002; Pannell et al., 2006).

Reflecting aggregate adoption, diffusion paths of agricultural technology are generally assumed to follow an S-shaped pattern over time (Griliches, 1957; Rogers, 1962; Sunding & Zilberman, 2000; Fernandez-Cornejo & McBride, 2002; Brethour & Weersink, 2003; Weersink & Fulton, 2020). A slow rate of diffusion is observed initially as early adopters accept the new technology, followed by a rapid increase as adoption of the technology spreads through the industry, tapering off as it reaches its upper limit (Fernandez-Cornejo & McBride, 2002; Weersink & Fulton, 2020). As diffusion is commonly measured either as the proportion of total farms or the share of total land using the innovation, peak adoption is constrained between 0% and 100% (Griliches, 1957).

Justifications for the S-shaped path commonly centre around imitation or threshold models in the literature (Sunding & Zilberman, 2000). Imitation models of diffusion paths assume technology spreads via communication with others in the industry. As a result, initial increases in marginal diffusion rates level off as the market becomes saturated with better informed producers (Sunding & Zilberman, 2000). Threshold models assume adoption occurs above some threshold level of producer heterogeneity (Sunding & Zilberman, 2000). When farm size is the source of this heterogeneity, the marginal diffusion rate reflects the fraction of farms that adopt at a particular point in time, and this rate initially increases but eventually declines as higher market penetration is achieved (Sunding & Zilberman, 2000).

2.3.2 General determinants of agricultural technology adoption

A large volume of literature focuses on identifying the factors influencing adoption of new agricultural technologies and quantifying their effects. Several studies (Rogers, 1962; Batz et al., 1999; Fernandez-Cornejo & McBride, 2002; Pannell et al., 2006; Weersink & Fulton, 2020) point to the characteristics of the technology itself as significant influences on its adoption. Specifically, the adoption of a new technology is hypothesized to be influenced by five of its attributes: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1962).

Pannell et al. (2006) and Weersink and Fulton (2020) aggregate these attributes into the relative advantage and trialability, encompassing compatibility in relative advantage, observability in trialability, and complexity as a factor of both. In this context, relative advantage refers to the extent to which the new technology is an improvement over the existing systems (Weersink & Fulton, 2020). This characteristic is a function of farm and agro-ecological characteristics, as well as the degree to which it aids farmers in reaching their goals (e.g., wealth and financial security, environmental protection, social approval, etc.) (Pannell et al., 2006; Weersink & Fulton, 2020). Trialability reflects both the ability to test the new technology and the quantity of additional information to be gained from trials (Pannell et al., 2006; Weersink & Fulton, 2020). Weersink and Fulton (2020) also include social, cultural, and personal networks as factors impacting the adoption of new technologies. These networks represent the roles that social networks and cognitive abilities play in producers' adoption decisions (Weersink &

Fulton, 2020). From these characterizations, one is able to identify the influential attributes unique to specific technologies.

The relative importance of each of these factors depends on the stage of the individual adoption process. Social networks have the largest impact in the early stages of adoption, as informal (e.g., family, community) or formal (i.e., extension services) networks contribute to producers' awareness and perceptions of a new technology (Weersink & Fulton, 2020). In the trial evaluation stage, the trialability of a new technology is the most important factor, where technologies that are difficult to trial face reduced likelihood of adoption (Pannell et al., 2006). Further, when the uncertainty reducing information gleaned from trials is limited, a technology faces an increased risk of remaining unadopted (Weersink & Fulton, 2020). In the later stages of adoption, an innovation's relative advantage is the critical factor. Farmers adopt, revise, and disadopt technology based on changes in the relative profitability (Weersink & Fulton, 2020).

2.3.3 Crop variety characteristics and adoption

In the crop variety literature, many studies have sought to identify the key factors that contribute to successful adoption (Barkley and Porter, 1996; Dahl et al., 1999; Fernandez-Cornejo & McBride, 2002; Dalton, 2004; Abadi Ghadim et al., 2005; Asrat et al., 2010; Cavatassi et al., 2011; Abebe et al., 2013; Michler et al., 2018). A general emphasis is placed on the end-use and production attributes of the new variety. In some cases, the influences of producer characteristics, such as farm size and farmer education, are also examined.

The importance of end-use factors appears to differ by crop. In their studies, Asrat et al. (2010), Abebe et al. (2013), and Michler et al. (2018) include end-use values in empirical analyses of adoption. For modern sorghum and teff varieties, Asrat et al. (2010) find that adoption does partially depend on the value of the output. Abebe et al. (2013) also consider market-value factors, finding that the marginal effect of improved stew quality for adoption of new potato varieties outweighs improvements in yields and disease resistance. Similarly, in adoption of improved chickpea varieties, Michler et al.'s (2018) results indicate that it is the market returns to new varieties driving adoption, even where yield remain unchanged from previous varieties. However, Dalton (2004) suggests that in addition to post harvest characteristics, the impacts of production traits should be considered.

The role of the agronomic traits of different varieties in the variety decision process generally centres on the comparative advantage and profitability. Dahl et al. (1999), Wale and Yalew (2007), and Asrat et al. (2010) examine these for wheat, coffee, and sorghum and teff varieties, respectively. Each point to disease tolerance, yield potential and stability, as well as resilience in various environments as key factors, although the significance of traits as factors depends on crops and regions. Further, Dalton (2004) finds that for rice varieties in Western Australia, it is the plant maturity rate and height that help explain producer willingness to pay for new varieties.

2.3.4 Determinants of wheat variety adoption

Barkley and Porter's (1996) study of the Kansas wheat industry is one of two key papers that examine the determinants of wheat variety adoption in North America. Dahl et al.'s (1999) work comparing the adoption of hard red spring wheat in Western Canada and North Dakota is the second. More recent studies in this area focus on developing countries, but these regions often experience differences in determinants from OECD countries as farmers face different economic conditions (Dixon et al., 2006; Di Falco et al., 2011; Gebresilassie & Bekele, 2015).

Barkley and Porter (1996) use an input characteristic model and pooled regression analysis to identify the key determinants of spring wheat variety demand between 1974 and 1993. They find that Kansas wheat producers account for end-use values and production characteristics when deciding which varieties to plant (Barkley & Porter, 1996). Relative yield, yield stability (measured as yield variance), and past production decisions significantly impact these adoption decisions (Barkley & Porter, 1996). Further, Barkley and Porter (1996) find evidence of a significant trade-off between desirable wheat characteristics as increases in traits such as yield potential may also lead to higher variations in realized yields.

Following a similar approach, Dahl et al. (1999) find differences between North Dakota and Western Canada spring wheat variety determinants. In North Dakota, economic factors such as end-use qualities carry more weight than the agronomic traits of varieties (Dahl et al., 1999).

However, results for Western Canada differed, with economic factors insignificant in the empirical analysis (Dahl et al., 1999). They point to the observed higher concentration of acres in the top variety reducing the variability in end-use quality as a possible explanation for this outcome (Dahl et al., 1999). Further, tighter Canadian regulations on new variety releases that also serve to minimize the variation in end-use quality may contribute to the lack of significance in producer decisions (Dahl et al., 1999).

Covey (2012) employs the approaches of these papers to identify key adoption factors of CWRS wheat in Saskatchewan. This analysis finds significant effects of a variety's expected yield, rate of maturity, age, and resistance to disease attributes on its adoption rate (Covey, 2012). Covey (2012) notes that the number of varieties on the market also significantly impacts adoption rates.

Each of these three papers use pooled data econometric approaches to examine wheat variety adoption. However, Baltagi et al. (2003) note that such approaches face potential bias by neglecting the panel nature of the data. Standard panel data approaches (i.e., the fixed effects and random effects models) come with their own limitation.[4] Hausman and Taylor (1981) and Pesaran and Zhou (2018) propose additional panel data approaches as potential solutions: the Hausman-Taylor instrumental variable model and the fixed effects filter model, respectively. To date, neither of these econometric approaches is widely used in the crop technology adoption literature; the latter due to its relative newness, the former due to challenges associated with its additional assumptions.

2.3.5 The role of adaptability in variety adoption

The adaptability of a crop or variety has long been studied, primarily in the agronomy literature (Nor and Cady, 1979; Chloupek & Hrstkova, 2005; Roy & Kharkwal, 2004; Sikder, 2009). The agricultural economics literature on variety adaptability is smaller, but considers its role in adoption. Variety adaptability is closely related to yield stability, however, there is a slight distinction between these two terms in the literature. Asrat et al. (2010) define adaptability as the

[4] Chapter five of this thesis provides a detailed discussion of several available econometric approaches, including their respective advantages and disadvantages.

ability of a variety to remain resilient under environmental stresses resulting from various factors such as soil quality, drought, or frost. Yield stability refers to the ability of a variety to produce consistent yield every year, regardless of crop disease and pest problems (Asrat et al., 2010). Similar definitions used by the agronomy literature more succinctly note that adaptability reflects performance variations across locations, while stability refers to variations across years (Roy & Kharkwal, 2004).[5] Given the trade-off between different variety attributes found in Barkley and Porter (1996), combined with the risk averse nature of farmers, the question of how important yield stability and yield adaptability are to adoption decisions arises. Higher yield potential improves profit prospects, but if it comes at the cost of decreased yield stability or varietal adaptability, farmers may be less inclined to adopt the variety.

Asrat et al. (2010) examine this and find that Ethiopian sorghum and teff farmers are willing to forego increase yield prospects if it means improved environmental adaptability and yield stability. Similarly, Wale and Yalew (2007) determine that farmers facing higher challenges in obtaining a subsistence income level prefer varieties with better environmental adaptability and yield stability over increased yield. Further, Coromaldi et al. (2015) note that non-adopters of improved varieties in Uganda tend to do better than adopters, as a result of the relatively higher adaptability features of the traditional local varieties. In general, it appears that risk vulnerable farmers prefer adaptable seeds with stable yields over the potential gains from higher yielding new varieties.

North American farmers are unlikely to be subsistence farmers. This means that the roles of a variety's adaptability and its yield stability may differ from developing countries. Several studies include yield stability, generally measuring it as the yield variance (Barkley & Porter, 1996; Barkley et al., 2010; Diffenbaugh et al., 2012). However, few consider the importance of adaptability in North American farming decisions, at least as it differs from yield stability.[6] Torshizi (2015) does so, building the concept of adaptability into a model of Canadian canola adoption. The degree of specificity (the inverse of adaptability) reveals the interaction between land characteristics and seed variety performance (Torshizi, 2015). Using this measure, Torshizi

[5] Chapter four of this thesis provides a more in-depth discussion of yield adaptability and stability.

[6] Most papers use yield variance to reflect all yield variations. This captures what is referred to here as yield stability, but as chapter four explains in more detail, this variance captures variations over time and not necessarily across locations.

(2015) finds that adaptability plays a key role in the adoption of canola varieties in Canada. Varieties with higher degrees of specificity attain less market share than those able to perform well in a wider range of environments (Torshizi, 2015). However, this does not mean that highly specific varieties are not useful; such varieties are necessary and beneficial in locations where conditions are highly specific (e.g., high rainfall location) (Roy & Kharkwal, 2004). To date, no studies look specifically at the role of adaptability in Canadian wheat variety adoption decisions.

Chapter 3: Conceptual framework

3.1 Introduction

To explain the relationship between the adaptability of a variety and its adoption, I develop a conceptual framework that draws from the theory of the firm, specifically Hotelling's (1929) seminal work on modeling product differentiation. I draw from recent applications of that work by Fulton and Giannakas (2004), Malla and Gray (2005), Torshizi (2015), and Hosseini et al. (2017). My main assumption is that wheat producers seek to maximize their returns through variety selection tailored to their growing conditions. Central to this decision – and the focus of this research – is the adaptability of varieties to various climate and soil conditions.

This chapter begins with a brief review of some of the literature on conceptual frameworks for agricultural technology adoption. Following this, I develop the conceptual framework for this thesis.

3.2 Literature on adoption conceptual frameworks

Selecting a conceptual framework is important when attempting to understand which attributes of a new agricultural technology influence the extent of market share that is captured. As Lindner (1987) points out, reduced explanatory power or contradictory findings are frequently the result of failure to employ a sound conceptual framework prior to empirical analysis. These frameworks set out the objectives, choices, and constraints faced by potential technology adopters and better inform empirical model specifications and interpretations.

The literature in this area generally employs either a profit maximization (Barkley & Porter, 1996; Greene et al., 1996; Abadi Ghadim & Pannell, 1999; Dahl et al., 1999; Barkley et al., 2010; Michler et al., 2018), or a utility maximization framework (Batz et al., 1999; Wale & Yalew, 2007; Asrat et al., 2010; Coromaldi et al., 2015). Both approaches have their merits, although profit maximization appears to be more widely used. Under a profit maximization framework, producers adopt a new variety when their net returns are higher, relative to their current process. Such net returns in agricultural technology adoption generally depend on land allocation, production technology, and the prices of both inputs and outputs (Abadi Ghadim & Pannell, 1999; Michler et al., 2018).

The simplest form of this economic framework, the static profit optimization model, considers a farmer whose objective is to maximize their profits in the current period only. Abadi Ghadim and Pannell (1999) represent this decision problem in the context of a farmer deciding how much land to allocate to a new crop, chickpeas. Here, chickpeas are allocated land when profits, in this case depending on the gross margins of both crops and the associated fixed costs, are greater than when zero land is allocated to chickpeas (Abadi Ghadim & Pannell, 1999). In the optimum, this implies that a new crop is adopted when its average gross margin less its fixed costs per acre are greater than when all land is allocated to the alternative crop (Abadi Ghadim & Pannell, 1999). However, this neglects to take into consideration the uncertainty farmers face regarding costs, environment, and production as well as the timeline of the adoption process.

As Weersink and Fulton (2020) point out, agriculture producers do not know the impacts on production and costs when initially considering investing in a new technology. Nor do they know with certainty which disease, pest, and climate conditions they will face during the growing season when they make their decisions. Further, farmers' subjective perceptions of a new technology's performance may change over time as additional information becomes available through the diffusion process and uncertainty surrounding it is reduced (Feder & O'Mara, 1981). These aspects of agriculture production necessitate the inclusion of risks associated with the innovation, as well as the use of a dynamic economic framework.

Abadi Ghadim and Pannell (1999) address these issues, expanding their framework to consider dynamic uncertainty, and later to include risk preferences and perceptions. Their dynamic profit function takes into consideration increases in farmer efficiency and the adoption process by expanding the profit function to include the net returns in the current period, as well as the sum net present value of net returns in future periods (Abadi Ghadim & Pannell, 1999). Incorporating uncertainty into this profit maximization framework means that it is now the expected profits being maximized. Under this approach, trialing the crop or variety in the first period reduces the subjective uncertainty farmers face surrounding the gross margin of the new technology in subsequent periods (Abadi Ghadim & Pannell, 1999). Even if the farmer does not undertake his own trial, information generated by the experiences of those who do will diminish this uncertainty over time (Feder & O'Mara, 1981).

Risk attitudes also play a role in profit optimization. Noting that farmers are most commonly risk averse, Abadi Ghadim and Pannell (1999) suggest that incorporating risk attitudes and utilities in adoption frameworks improves the accuracy of predictions. To incorporate such attitudes, Barkley et al. (2010) use portfolio theory. Applied to agriculture, farmers may choose to plant multiple varieties on different fields to reduces potential yield losses in much the same way that a business investor diversifies their stock portfolio to minimize their risk. To model this, Barkley et al. (2010) develop an expected profit maximization framework that accounts for the yield risks of each variety of wheat, using an input characteristic model (ICM) derived from the theory of the firm. In their economic model, expected profits depend on the output price, expected output, input costs, and yield variability cost. Demand for a given variety is a function of the output prices, own and substitute seed prices, the cost of yield variability, and the agronomic characteristics of the variety. This approach parallels those of Barkley and Porter (1996) and Dahl et al. (1999), however, Barkley et al.'s (2010) study goes further by developing a mean-variance efficiency frontier using the average yield, yield variance, and pairwise co-variances of varieties. They find that portfolio strategies can significantly reduce the risks faced by Kansas wheat growers.

Weersink and Fulton (2020) counter that profit maximization neglects early-stage decisions as the new technology is first introduced. Considerations, such as the relative advantage, trialability, and farmers social networks impact adoption of innovations and conceptual models should consider these factors and their timing when determining adoption rates (Weersink & Fulton, 2020). Weersink and Fulton (2020) note that if these non-economic factors are expected to negatively (positively) impact the adoption rate, predictions under traditional profit maximization theory will be upper (lower) bounds.

Coming out of the literature on the theory of the firm, several studies in the agricultural economics literature have applied the concepts of Hotelling's (1929) product differentiation models to crop technology decisions. Fulton and Giannakas (2004) use a vertical differentiation-based framework to understand behaviours and welfare effects for three scenarios related to genetically modified product labeling. Hosseini et al., (2017) study the incentives for signing cross-licensing agreements when each firm has multiple horizontally differentiated products. More specific to crop varieties, Malla and Gray (2005) use a two-stage game theory-based framework to look at the dynamics of public and private investments in variety development, where varieties are horizontally differentiated products. Finally, Torshizi (2015) develops a conceptual framework that considers *n* horizontally differentiated canola varieties and the dynamics between certain characteristics and producer variety choices. Expanding on this and Hotelling's (1929) models, Torshizi et al. (2018) investigate the role of the relationship (correlation) between the differentiating characteristics of two consumer products and consumer's ranking of one relative to the other, subsequently identifying the equilibrium conditions.

3.3 Framework

As wheat producers seek to maximize their returns, the first consideration is a variety's yield. This yield depends on the attributes of the variety, including its disease tolerance, yield potential, and adaptability to various growing conditions. In this conceptual framework I consider the role of adaptability in the adoption of two competing varieties that are horizontally differentiated with respect to their drought/moisture tolerance. As mentioned previously, adaptability is the ability of a variety to perform consistently across various locations or growing conditions (Roy & Kharkwal, 2004; Asrat et al., 2010).

Yield curves for varieties 1 and 2 are shown in Figure 3.1, an adaptation of Hotelling's (1929) model of horizontal differentiation. The horizontal axis represents location in the characteristic space, scaled between 0 (the location with the lowest soil moisture level) and 1 (the location with the highest soil moisture level). The vertical axis measures yield levels. While variety 1 is designed to perform well in dry soil (i.e., on the left side of Figure 3.1), variety 2 is bred for locations with high soil moisture levels (i.e., on the right side of Figure 3.1). Variety 1 (2) reaches its yield potential ($\hat{y}$) at the lowest (highest) moisture point 0 (1). The difference in response to soil moisture levels for these two varieties results in different degrees of adaptability, as represented in different slopes for their yield curves (i.e., different rates of reduced performance as area expands beyond the optimal location).

These varieties are available for sale to $f = 1, \dots, F$ farmers located on the horizontal axis. Each farmer owns one parcel of land (i.e., each farmer purchases one unit of seed). These parcels of land differ with respect to one characteristic (i.e., soil moisture). As it is conventional in Hotelling-type models (e.g., Fulton and Giannakas (2004), Malla and Gray (2005), Hosseini et al. (2017), Torshizi (2015), and Torshizi et al. (2018)), I rank the locations based on their moisture level so that the corresponding yield levels are in descending (ascending) order.

Each farmer makes a binary decision between growing variety 1 or variety 2. [7] Following Torshizi (2015) and Torshizi et al. (2018), I assume that yield levels of variety i have a uniform distribution between the maximum and minimum yield levels (i.e., $y_i \sim u(\hat{y}, \hat{y} - \mu_i)$). As a result, variety 1 performs best for the farmer located at 0 (i.e., dry soil location), variety 2 performs best for the farmer located at 1 (i.e., moist soil location), and yield per acre is linearly declining as area expands (i.e., as I move away from the variety's optimally ranked farmer, the yield per acre declines due to increasingly less optimal soil moisture).[8] Further, to simplify the model, I assume the yield potentials and costs of seeds for both varieties are equal.[9] Then, the yield per acre of variety i (yield curve) is:

$$y_i = \hat{y} - \mu_i x_f \,, \tag{3.1}$$

where $i = 1,2$, $\hat{y}$ is the yield potential of each variety, μ_i is the degree of specificity of variety i, and x_f is the distance of farmer *f* from the top ranked location for variety i.[10] Here, yield potential refers to the yield of each variety on its optimal land parcel. Therefore, yield for variety 1 is greatest for the farmer located at 0, and is diminishing linearly with the rate of its degree of specificity as one moves towards location 1. Similarly, variety 2's yield declines as one moves

[7] At the time of variety decisions, the farmer has already decided to produce wheat on their parcel of land. Therefore, farmer's only decision is selecting which of the two varieties available to use.

[8] Torshizi et al. (2018) show that this linearity is the result of "the implicit assumption of perfectly correlated preferences in the original Hotelling model" (p. 1). When the characteristics, or the buyers' preferences for them, are imperfectly correlated, this linearity does not hold.

[9] The model can be extended to allow for differences in yield potential and seed costs. However, to focus on the impact of changes in adaptability on adoption, I choose to use these simplifying assumptions.

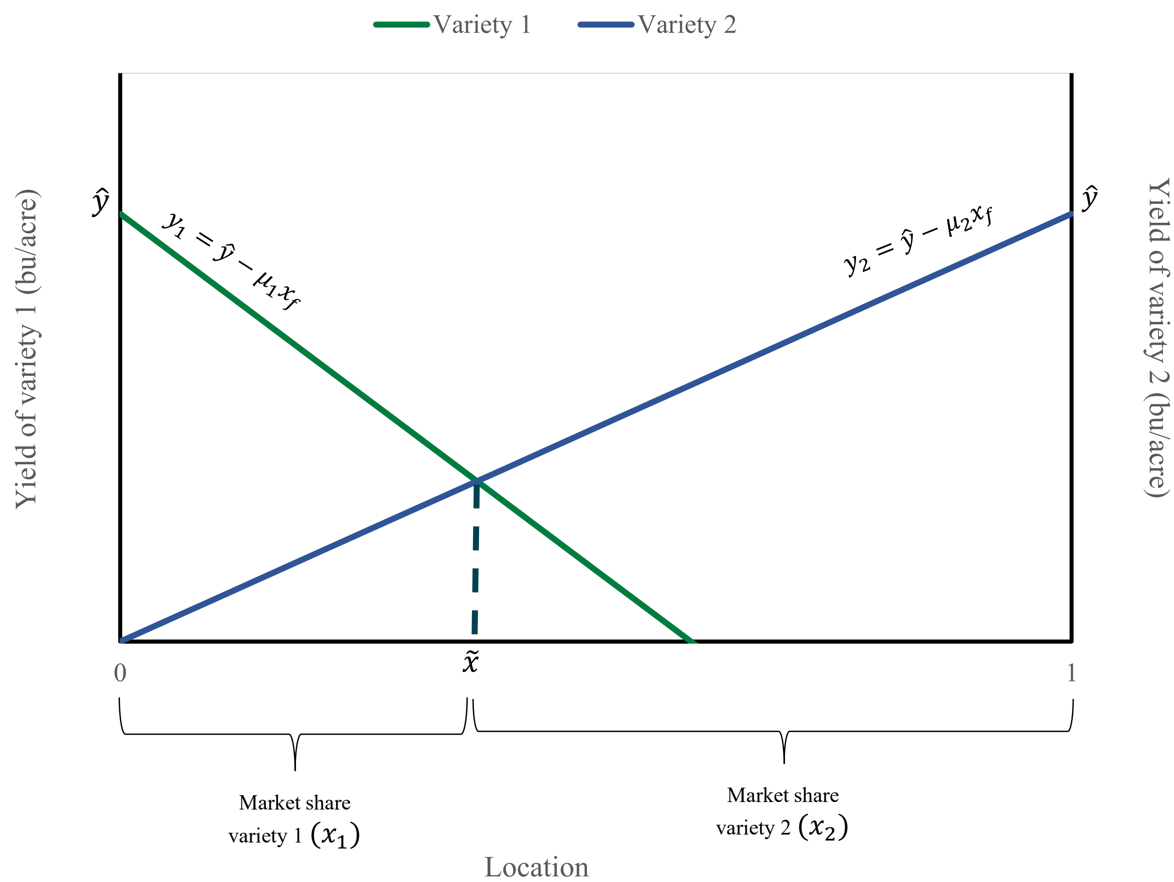
[10] For variety 2, this is measured as $(1 - x_f)$ in the adapted Hotelling (1929) model.

from location 1 towards location 0. Implied by Equation (3.1), a more rapid decline in overall yield per acre is observed for the less adaptable variety (i.e., greater μ).

This is illustrated in Figure 3.1, where the yield curves for both varieties are shown in an adaptation of Hotelling's (1929) model of horizontal differentiation. I assume that variety 1 is less adaptable to shifts in growing conditions (e.g., soil moisture) than variety 2 ($\mu_1 > \mu_2$).[11] In Figure 3.1, $\tilde{x}$ represents the indifferent farmer who, based on her "location", obtains the same yield regardless of the variety she chooses. It is important to note that $\tilde{x}$ does not represent an actual geographic location. Rather, it is the ranked land parcel (or farmer) where the varieties' yield performances are equal based on the specified yield curves. Farmers located to the left of $\tilde{x}$ face growing conditions that lead them to select variety 1 as the yield per acre is higher than it is for variety 2. Likewise, farmers located to the right of $\tilde{x}$ select variety 2 for its relatively higher yield in their growing conditions. Therefore, x_1 and x_2 represent the respective market shares of each variety, with the more adaptable variety 2 capturing a larger portion of the market.

[11] This assumption generates a steeper yield curve for variety 1, stemming from a higher degree of specificity that reduces the marginal gains in yield of increasing acreage allocated to this variety.

Figure 3.1: Hotelling's linear city applied to wheat variety adoption and adaptability



Following Perloff and Salop (1985), Torshizi (2015), and Torshizi et al. (2018), to determine demand (adoption) for each variety, I adopt a surplus maximization approach,[12] where surplus is a function of these yield curves. I specify surplus from variety *i* to farmer *f*, located at x_f as:

$$s_{fi} = Py_i(x_f) - w\,, \tag{3.2}$$

[12] Alternatively, I could use a profit maximization approach; however, because the fixed costs associated with switching between wheat varieties is negligible, it is both simpler and more accurate to shift to producer surplus maximization under perfect competition. While switching between different crops may require the purchase of new equipment and incurring other fixed costs, production methods for varieties within the same crop type (e.g., wheat) are generally similar enough that such costs are minimal (Dahl et al., 1999). There may be small costs of learning (e.g., how the variety actually performs on their land, changes in maturing time impacting harvest) but given that most varieties would not substantially vary in this respect, such fixed costs could reasonably be assumed to be zero.

where P is the per unit value of output, yield per acre is a function of location x_f, as defined in equation (3.1), and w is the cost of seeds to the farmer, previously assumed to be the same for both varieties. Adding the assumption that wheat production is perfectly competitive (i.e., famers are price takers), total surplus across producers is the sum of the surplus accruing to each individual farmer located between 0 and 1 (Figure 3.1). Further, I assume total land area is $\bar{X} = x_1 + x_2 = 1$. [13] The aggregate producer surplus optimization problem is:

$$Max_{x_1,x_2}\, S = \sum_{f=1}^{F} s_{fi} = P\left(\int_0^{\tilde{x}} (\hat{y} - \mu_1 x_1)dx + \int_{\tilde{x}}^{1} (\hat{y} - \mu_2 x_2)dx\right) - w(x_1 + x_2\,) \tag{3.3}$$

$$subject\ to\ x_1 + x_2 = 1\,,$$

where x_i reflects total parcels of land allocated to variety *i* across all wheat producers and all other variables are as previously defined. This constraint is assumed to be binding, implying that all land allocated to wheat production by producers is used for either variety 1 or variety 2. To simplify, normalize the output price to $P = 1$, which results in the following Lagrangean:

$$Max_{x_1,x_2,\lambda}\, L_s = \int_0^{\tilde{x}} (\hat{y} - \mu_1 x_1)dx + \int_{\tilde{x}}^{1} (\hat{y} - \mu_2 x_2)dx - w(x_1 + x_2) + \tag{3.4}$$

$$\lambda(1 - x_1 - x_2)\,,$$

where λ is the shadow price of land. Taking first order conditions yields:

$$x_1^* = \frac{\mu_2}{\mu_1 + \mu_2} \tag{3.5}$$

and

$$x_2^* = \frac{\mu_1}{\mu_2 + \mu_1}\,, \tag{3.6}$$

where x_i^* reflects demand for variety *i*. Differentiating demand with respect to the degree of specificity of the respective variety, I find:

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[13] Alternatively, x_i may reflect the share of the market allocated to variety *i*, making the constraint on the sum more intuitive.

$$\frac{dx_1}{d\mu_1} = -\frac{\mu_2}{(\mu_1 + \mu_2)^2} < 0 \tag{3.7}$$

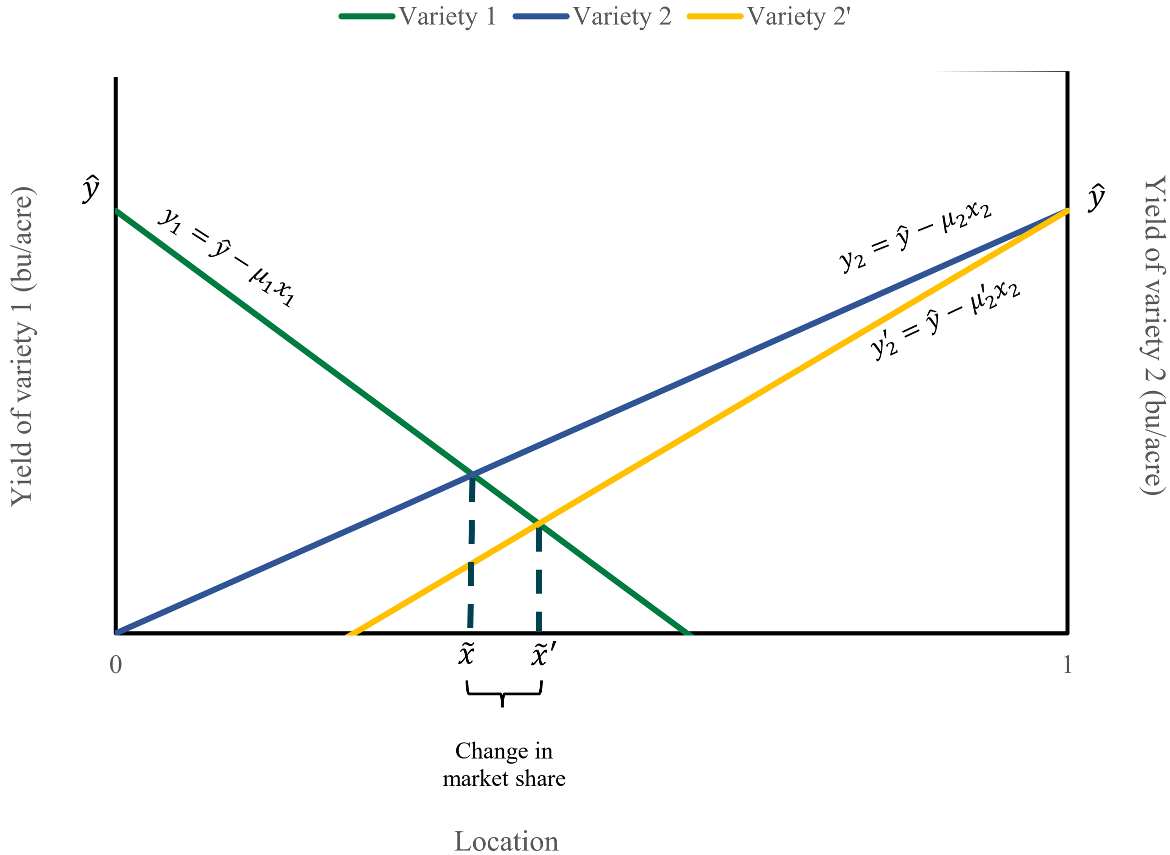
and

$$\frac{dx_2}{d\mu_2} = -\frac{\mu_1}{(\mu_2 + \mu_1)^2} < 0. \tag{3.8}$$

This shows that an increase in μ_i reduces x_i, *ceteris paribus*. That is, as a variety becomes less adaptable (i.e., higher degree of specificity) to variations in growing conditions, wheat producer demand for that variety declines. From this, I expect to find a negative impact from increases in the degree of specificity on adoption in my empirical analysis.

Now consider a shift in local climate such that variety 2 becomes relatively less adaptable to these new growing conditions, while the performance of variety 1 is unaffected. This could occur if a decrease in local rainfall resulting from climate change disproportionally affects the less drought tolerant variety 2, for example. This increases the sensitivity of variety 2 to its growing conditions, thereby increasing its degree of specificity. As a result, the yield curve for variety 2 becomes steeper (y_2') and our indifferent farmer shifts from $\tilde{x}$ to $\tilde{x}'$ (see Figure 3.2). Demand for variety 2 declines, and a corresponding increase in market share for variety 1 is observed even though the yield potential for variety 2 remains unchanged in this model. This resulting reduced demand for variety 2 reflects our findings in Equation (3.8) regarding the relationship between a variety's adaptability and its adoption. Therefore, when growing conditions shift such that one variety is less capable of maintaining its performance across locations (i.e., more sensitive to a shift in climate), demand for this variety is expected to decline. To what degree depends on the magnitude of the change in μ_i and the relative adaptability of the other variety.

Figure 3.2: Hotelling's linear city applied to a shift in wheat variety adaptability



Chapter 4: The data

4.1 Introduction

This chapter describes the dataset and configurations for this thesis. This includes a complete account of the data sources and availability, as well as the construction process of the dataset that I use to examine the adoption behaviour of Western Canadian wheat producers. Observations on the distribution of wheat acreage across varieties follow this discussion. Finally, this chapter concludes by highlighting necessary data adjustments and some of the challenges of data collection for this project. Noting these complications is important, as unavailable and inconsistent data reporting presents obstacles for both Canadian wheat producers and researchers.

4.2 Data regions and sources

The data for this thesis comes from provincial publications intended to relay varietal information to farmers. Provincial Yield Magazines[14] provide insured acreage and yield data in their annual publications. Additional varietal traits are obtained from provincial Seed Guides[15] and varieties' ages from the Canadian Food Inspection Agency's (CFIA) [16] variety registration database. The resulting dataset containing spring wheat varieties ranges from 2009 to 20018 for Manitoba and Saskatchewan, and 2013 to 2018 for Alberta.[17] Aggregating this into a prairie-wide dataset containing both yield and non-yield trait data from all three provinces provides 1,230

[14] Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.), Saskatchewan Crop Insurance Corporation (n.d.)

[15] Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.), Saskatchewan Seed Growers' Association (n.d.)

[16] Canadian Food Inspection Agency (n.d.)

[17] Limited winter variety data is available in the full dataset. However, it is not used in the analysis of this thesis because the differentiated natures (i.e., different planting times, environmental factors, etc.) of winter and spring wheat varieties mean that variety selection processes are inherently different. As a result, winter wheat varieties require separate analysis but the limited available data (24 total observations) is not sufficient to conduct such an analysis. Therefore, this thesis focuses on spring wheat variety only, and all summary statistics exclude winter wheat variety data.

observations on 139 varieties, with 350 observations from Alberta, 319 from Manitoba, and 561 from Saskatchewan.

4.3 Construction of the data

Since the data for this thesis comes from several sources, it is important that I describe how I generate my final dataset for the sake of transparency and future research. Initially, I construct provincial datasets with the dependent variable, variety acreage, and the yield based explanatory variables derived from provincial Yield Magazine data. I explain the calculations for the latter variables in the discussion below. Following this, I discuss the collection of non-yield varietal traits such as disease tolerance, maturity rate, and varietal height from provincial Seed Guides. Next, I calculate variety age based on information from the CFIA and then present the process for matching up the corresponding observations from each of these sources to create complete provincial datasets. Finally, I explain the process of merging these datasets into an aggregated prairie-wide dataset and summarize each of the dependent and independent variables in Table 4.2.

4.3.1 Construction of the provincial datasets

In this section, I discuss the process for constructing the provincial datasets. This includes the calculation of the yield-based variables, as well as the process to obtain and configure the other varietal trait variables. Following this, I explain the determination of the indicator of varietal adoption. Concluding this section, I discuss the process for merging these variables into a single dataset.

4.3.1.1 Yield-based variables

The first step in constructing the provincial datasets is calculating four yield-based variables: yield potential, average yield, the degree of specificity, and yield variance. For Manitoba, this data is available at the rural municipality level, while Saskatchewan and Alberta report yields at the risk zone level. Moving forward, I refer to these municipalities and zones as risk areas.

Yield potential and average yield provide relative indicators of expected variety output for Canadian wheat farmers. Calculations for these two variables are straightforward. Yield potential is simply the maximum yield observed for a variety in a particular province and year. Similarly, average yield is the mean yield of that variety observed within a province in a given year. Provincial Yield Magazines provide the information for all insured acreage above a province specific threshold used in these calculations.[18]

Calculations for yield variance and the degree of specificity, both potential measures of variety adaptability, are slightly more complex. Variety adaptability is defined as "reduced variation in performance across locations" (Roy & Kharkwal, 2004, p. 573), or the interaction between genotype and location. Previous studies in agricultural economics, including Barkley and Porter (1996) use yield variance as the indicator of varietal adaptability, where lower variances indicate less volatile and therefore theoretically preferable varieties. I calculate this yield variance within a given year as:

$$s_i^2 = \frac{\sum(y_{ij} - \bar{y}_i)^2}{RA} \ , \tag{4.1}$$

where s_i^2 denotes the yield variance for variety i, y_{ij} indicates the observed yield of variety i in risk area j, and $\bar{y}_i$ is the average yield across the number of risk areas RA that variety i is planted in a given year. However, Torshizi (2015) argues that using the yield variance as an indicator of the adaptability of a variety is potentially misleading; it is possible that two varieties with the same yield variance are bred to respond to different growing conditions and have different adaptability levels (Torshizi, 2015). Consequently, Torshizi (2015) proposes an alternative measure of adaptability to yield variance that better captures this genotype × location interaction through considering the range of yields that a variety achieves across various locations. Referred to as the degree of specificity, this alternative measure reflects the slope at any point along the yield curve when yield levels are ranked in descending order (i.e., the rate of reduction in yield as area expands beyond the optimal growing location). As long as the uniform distribution assumption is met, the overall slope of the yield curve (i.e., its degree of specificity), as defined in chapter three, is:

[18] See section 4.5 for an explanation of these thresholds.

$$\mu_i = \frac{y_i^{max} - y_i^{min}}{RA} \ , \tag{4.2}$$

where μ_i is the degree of specificity and y_i^{max} (y_i^{min}) is the annual maximum (minimum) yield of variety i across risk areas RA. Since the degree of specificity reflects the mathematical inverse of adaptability, larger values indicate varieties that are less adaptable to various growing conditions (Torshizi, 2015). As chapter five discusses in more detail, I estimate two model forms in this thesis, one with yield variance and average yield, the other with the degree of specificity (alternatively referred to as variety specificity) and yield potential to compare the performance of each potential measure of adaptability.

4.3.1.2 Other variety trait variables

Following the calculation of these four yield variables, I collect data for non-yield varietal traits such as disease tolerance, maturity rate, and varietal height from the provincial Seed Guides. Each provincial dataset includes protein content, stem rust, leaf rust, stripe rust, loose smut, bunt, leaf spot, fusarium head blight, sprouting, lodging, height, head awn, maturity rate, and seed weight variables. Additionally, Alberta and Saskatchewan's datasets include test weight data.

For resistance (or tolerance) to lodging, sprouting, and diseases, each province reports on a five-category relative scale with slight variations in terminology by province and between years. Here, relative refers to the comparative rating each province gives a variety based on its performance on a select trait, relative to the check variety. Annual provincial publications update these ratings as knowledge about a variety's reaction to disease increases or if a variety shows a change in this reaction (Kirk, 2020b). For example, Saskatchewan rates tolerance from very poor to very good for 2009-2014, and susceptible to resistant for 2015-2018. Converting these for all provinces to numeric values on a 1 to 5 scale, where 1 indicates very poor or susceptible, I maintain the relative ratings while simplifying the data analysis process. The variables measured on these 1 to 5 scales are resistances to stem rust, leaf rust, stripe rust, loose smut, bunt, leaf spot, fusarium head blight, sprouting, and lodging.

Other variety traits collected from provincial Seed Guides differ slightly in measurement across the provincial datasets. For example, after some adjustments, protein content in Manitoba reflects the actual percentage, while the other two provincial datasets report the percentage content relative to a check variety.[19] Maturity rates in Alberta use a five-point scale similar to that of the disease tolerances, with 1 indicating relatively slower maturing varieties. However, Manitoba and Saskatchewan differ from this, instead reporting the number of days to maturity relative to the check varieties. Height and seed weight data again differ between the three Seed Guides. Data collected for Alberta reflects the actual height in centimetres, paired with the thousand kernel weight in grams. Saskatchewan's data provides both height and seed weight relative to the check variety, using centimetres and milligrams for respective units. Manitoba's height, again requiring some internal adjustments, is on a 1 to 4 scale, with 1 indicating shorter varieties. [20] Seed weight refers to the relative four-point scale used to report seed size in this third province. Finally, test weight is only available for Alberta (lb/bu) and Saskatchewan (relative kg/hl).

Each provincial dataset also includes assigned wheat classes, whether or not the variety has an awned (bearded) head, and the age of each variety. I convert head awn, reported as either yes or no in provincial Seed Guides, to a dummy variable where 1 indicates that a variety does have an awned head. For variety age, I use the CFIA variety registration database to identify the date of registration. With this information, I calculate the age of each variety in months at the time of selection. Since planting of wheat in Saskatchewan, the largest producer, generally occurs in May (He et al., 2012), I use April 30 of each year as the annual cut-off for variety selection in these calculations.

4.3.1.3 Adoption indicator and number of varieties available

Next, I calculate annual total insured acres of each variety based on risk area level data from the provincial Yield Magazines. This data represents the adoption level for each wheat variety, used

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[19] The reporting format for protein in Manitoba shifts after 2012, thereby requiring some adjustments to obtain a consistent measurement over time. For further details on these adjustments, see section 4.5.
[20] The reporting format for height in Manitoba shifts after 2010, thereby requiring some adjustments to obtain a consistent measurement over time. For further details on these adjustments, see section 4.5.

as the dependent variable in this thesis. I also calculate the provincial shares of insured acres allocated to each variety. However, each province only reports yield and acreage data for varieties planted above a threshold level of insured acres or producers in the respective risk areas. I outline the impacts of this limitation on data availability in more detail in section 4.5.

One final variable included in the provincial data sets is the number of varieties considered available on the market. Although not used directly in the regression models, this piece of information is useful in understanding the distribution of wheat acreage across varieties and therefore included in the provincial datasets. For consistency in the measure across provinces and due to data availability, the number of varieties available reflects the annual number of varieties that report yield data in a province. This means that for a variety to be counted as available in a given year, it must be planted on insured acres above the minimum threshold for each province. As a result, this number does not fully reflect all varieties officially registered each year. However, seed distributors are unlikely to actively carry all varieties officially registered, as some have been registered for over 30 years. For this reason, using the annual number of varieties listed in the Yield Magazine more closely reflects what is actually available to farmers, compared to the number of varieties registered to be grown in these three provinces.

4.3.1.4 Merging variables into provincial datasets

Following the calculations and collection of both yield and non-yield varietal trait variables, I merge these observations into a single dataset for each province. This process entails matching available data from all three sources: provincial Yield Magazines, provincial Seed Guides, and the CFIA variety registration database. Complicating this process is that in several cases, corresponding yield and non-yield trait data are unavailable. This is likely in part due to Canada’s variety registration system (Kirk, 2020a), which I explain further in section 4.5. However, due to their relative nature of measurement, non-yield attributes vary little over time. Therefore, farmers may refer to previous publications when Seed Guide data for a particular existing variety is unavailable in the latest edition. Assuming this is the case, I fill missing non-yield trait data with data from the next closest previous edition.[21] This improves the size of the provincial level datasets by 37 observations for Alberta, 28 for Manitoba, and 78 for Saskatchewan.

4.3.2 Construction of the aggregate prairie provinces dataset

The aggregate prairie provinces dataset contains all three provincial datasets. In order to be able to empirically examine variety adoption using this larger dataset, I add a province identifier variable and adjust three other variables:

(1) Height,
(2) Protein content,
(3) Maturity rate.

All three prairie provinces report slight variations of these variables, making the adjustments outlined below necessary to obtain consistent measurement.

Since Manitoba's dataset measures variety height on a four-point scale, I convert Alberta and Saskatchewan's heights to the same unit of measurement. This is done by shifting Saskatchewan's heights from a relative measure to actual centimetres using information on the check varieties, converting heights for both provinces to inches, and then assigning the height ratings in line with Manitoba's. In this case, I assign heights less than 27.75 inches a value of 1, indicating relatively shorter varieties. Height ratings of 2 indicate varieties between 22.75-33.49 inches, and ratings of 3 indicate heights of 33.5-39.24 inches. Relatively tall varieties are those 39.25 inches or taller, assigned a value of 4.[22]

Similarly, protein content is reported at percentage levels in Manitoba, but relative to a check in the other two provinces. However, check variety protein contents are available in both

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[21] Missing non-yield varietal trait data is only filled forwards in time (i.e., only where variety data is available in at least one of the previous years). The same argument of farmers referencing an early edition does not apply where varietal data is only available in later years and therefore does not exist prior to those years.

[22] Heights in Manitoba range from 22 inches to 45 inches. Thresholds for each rating on the four-point scale were determined by dividing this range into four intervals of 5.75 inches. This same scale is then applied to Alberta and Saskatchewan.

Alberta and Saskatchewan's Seed Guide data. Using these, I shift protein for both provinces to the actual percentage content.

Alberta's reported maturity rate which uses a five-point scale similar to disease tolerances means that maturity rates for Saskatchewan and Manitoba must be shifted to a similar scale. However, due to differences in growing season lengths across these three provinces, what constitutes early maturity in one province is not necessarily early in another. To address this, I first shift Saskatchewan and Manitoba from relative days to maturity to the actual number of days. Then, using a variety common to all three provinces, I centre the five-point scale for each province on AC Barrie's maturity rate. Common to all three provinces, AC Barrie is reported at 106 days to maturity in Alberta, 100 in Saskatchewan, and 99 in Manitoba. Table 4.1 provides further details on the division into maturity ratings. Using this structure maintains relative performances within provinces while providing consistent units in the aggregated dataset.

Table 4.1: Conversion of days to maturity to five-point scale for Manitoba and Saskatchewan

Scale value	Manitoba		Saskatchewan	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
1	102		104	
2	100	101	102	103
3	98	99	99	101
4	96	97	97	98
5		95		96

4.3.3 Summary

Figure 4.1 provides a brief overview of the process of constructing the aggregated dataset for the Canadian Prairies. For simplicity, this dataset is used in all modeling for chapter five, with the provincial identification variable employed to filter by province where required. This is to prevent multiple units for each variable complicating the discussion of the empirical results. Table 4.2 summarizes each of these variables in the aggregate prairie provinces dataset, including short definitions and sources.

Figure 4.1: Construction process for the aggregate dataset for the Canadian prairie provinces

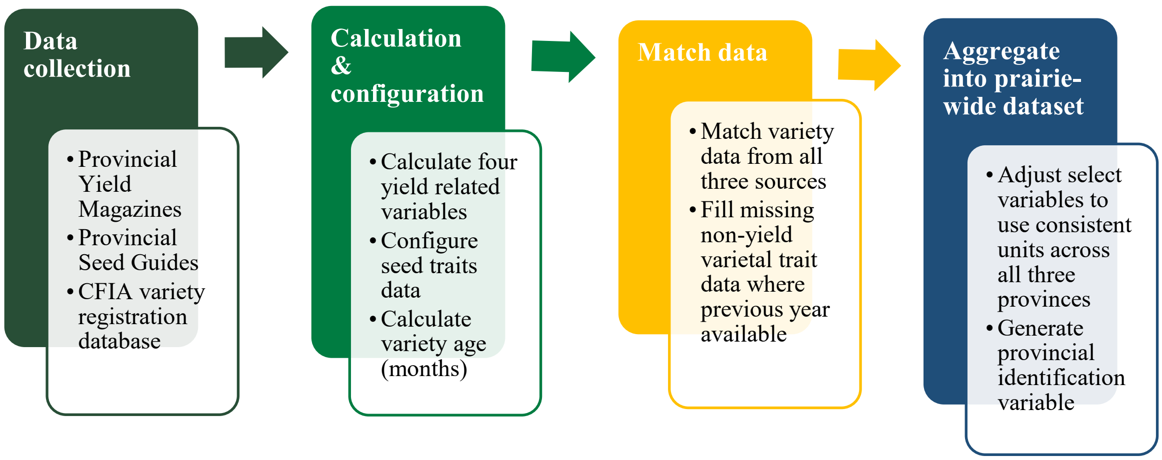


Table 4.2: Description and sources of variables in the aggregate prairie provinces dataset

	Variable	Description	Source(s)
Adoption indicators	Acres	Total insured acres allocated to a variety in a given year (acres).	Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.), Saskatchewan Crop Insurance Corporation (n.d.)
	Share	Share of total insured acres allocated to a variety in a given year (%).	
Yield variables	Yield potential	Maximum reported yield across risk areas for a variety in a given year (bu/acre).	
	Average yield	Average reported yield across risk areas for a variety in a given year (bu/acre).	
	Yield variance	Variance of reported yields across risk areas for a variety in a given year ((bu/acre)^2).	
	Degree of specificity (or variety specificity)	The degree of specificity for a variety in a given year (the inverse of adaptability).	
Tolerances (or Resistances)	Lodging	Relative scale rating of the variety's resistance (1-5)	Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.), Saskatchewan Seed Growers' Association (n.d.)
	Sprouting	Relative scale rating of the variety's resistance (1-5)	
	Stem rust	Relative scale rating of the variety's resistance (1-5)	
	Leaf rust	Relative scale rating of the variety's resistance (1-5)	
	Stripe rust	Relative scale rating of the variety's resistance (1-5)	
	Loose smut	Relative scale rating of the variety's resistance (1-5)	
	Bunt	Relative scale rating of the variety's resistance (1-5)	
	Leaf spot	Relative scale rating of the variety's resistance (1-5)	
	Fusarium head blight	Relative scale rating of the variety's resistance (1-5)	
Other variables	Protein	Protein content of a variety (%).	Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.), Saskatchewan Seed Growers' Association (n.d.)
	Maturity	Relative scale rating of maturity for a variety (1-5).	
	Head awn	Dummy variable where 1 indicates head awned, and 0 indicates not.	
	Height	Relative height of plant scale rating (1-4).	
	Seed weight	Seed weight in thousand kernel weight for Alberta, relative milligrams to check variety in Saskatchewan, and relative scale rating of seed size (1-4) in Manitoba.	
	Test weight	Test weight in kg/hl for Saskatchewan, and bu/lb in Alberta.	
	Variety age	Number of months since a variety was registered with the VRO (months).	Canadian Food Inspection Agency (n.d.)

4.4 Observations from the data

In Table 4.3, I present summary statistics for annual total acres allocated to varieties in the full dataset, as well as the number of varieties considered available each year. Average total acres allocated to a particular variety varies by province, observed at over 76,000 acres in Saskatchewan, over 78,000 acres in Alberta, and nearly 69,000 acres in Manitoba. Aggregating to the prairie-wide level, average total acres for a given variety is approximately 75,000. However, the high associated standard deviations for each of these averages point to large differences in adoption across varieties.

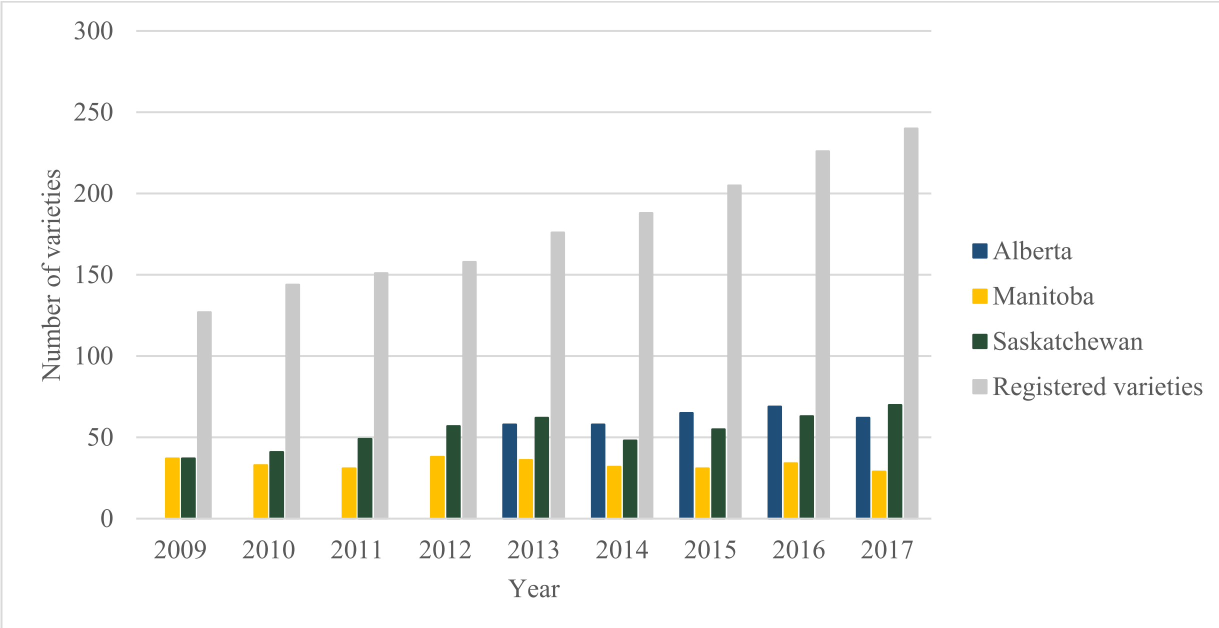
Table 4.3: Summary statistics for acres and number of varieties available

	Alberta		Manitoba		Saskatchewan		Aggregate prairie provinces	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
Total acres (acres)	78,095	149,348	68,976	164,161	76,729	152,101	75,107	154,473
Share of total provincial acres (%)	1.64	3.31	3.01	7.23	1.67	3.41	2.01	4.72
Number of varieties available	65.21	3.82	41.03	5.74	74.27	11.32	63.07	15.99

Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

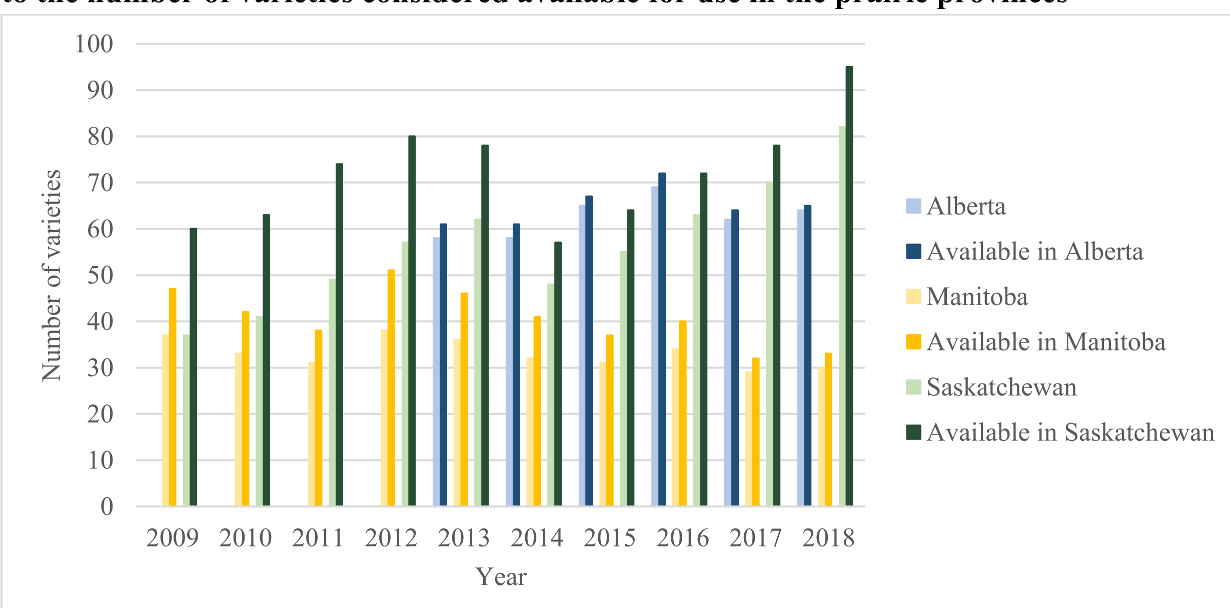
Such high standard deviations may stem from the differences between the number of varieties available and the number of varieties actually used each year. In Figure 4.2, it is clear that there is a substantial gap between the number of varieties registered for use relative to the number actually used in each province. This in itself is not overly surprising as several varieties are registered prior to 1980 and likely unavailable for purchase from seed distributors by 2009. Alternatively using the number of varieties considered available in each year based on Yield Magazines, the discrepancy is significantly smaller (Figure 4.3). However, this figure does not provide information regarding the distribution of acres across varieties, therefore neglecting to show the adoption rates of each particular variety.

Figure 4.2: Annual number of varieties adopted above the provincial threshold compared to the number of varieties registered for use in the prairie provinces



Sources: Canadian Food Inspection Agency (n.d.), Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

Figure 4.3: Annual number of varieties adopted above the provincial threshold compared to the number of varieties considered available for use in the prairie provinces



Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

Plotting the density function reveals that the distribution of acres across varieties is heavily skewed to the right (Figure 4.4).[23] In all three provinces, the majority of varieties are planted on fewer than 500,000 insured acres in any given year, while only a few varieties are more widely used. This distortion in distribution is also observable for the second indicator of adoption, the annual share of total provincial acres allocated to a particular variety. Considering the second density plot in Figure 4.4(a), it is apparent that very few varieties achieve a provincial market share of 20% or higher. In fact, it is only in the province of Manitoba (Figure 4.4(c)) that any varieties surpass 30% of provincial market share.

[23] This density function includes all observations over the entire 10-year span of the data. This means it ignores the panel nature of the data, treating all observations of acreage for each variety in each year separately.

Figure 4.4: Distribution of adoption across varieties and time measured in acres and share of provincial acres for each province and in aggregate

Figure 4.4(a): Adoption measured in acres

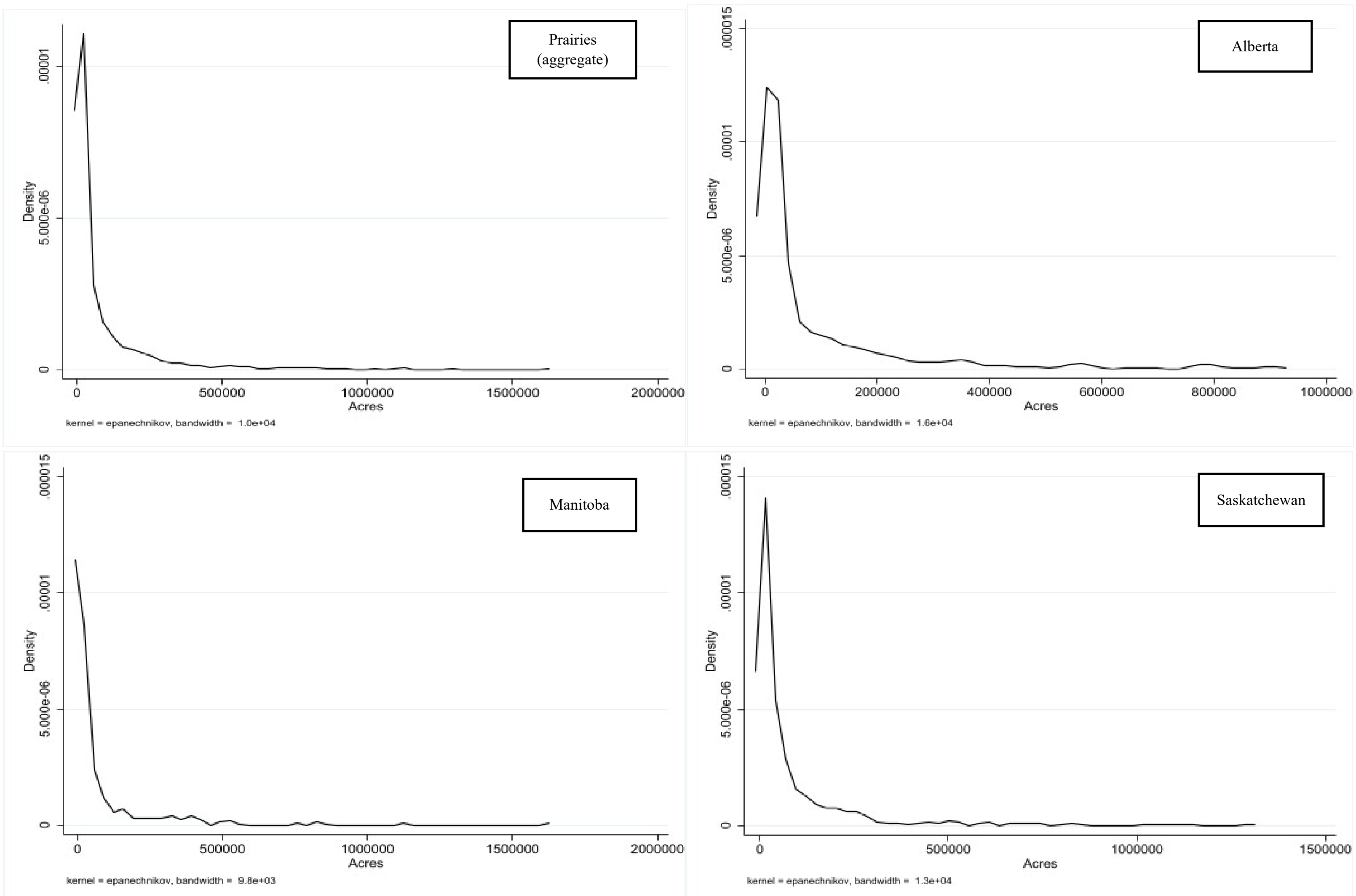
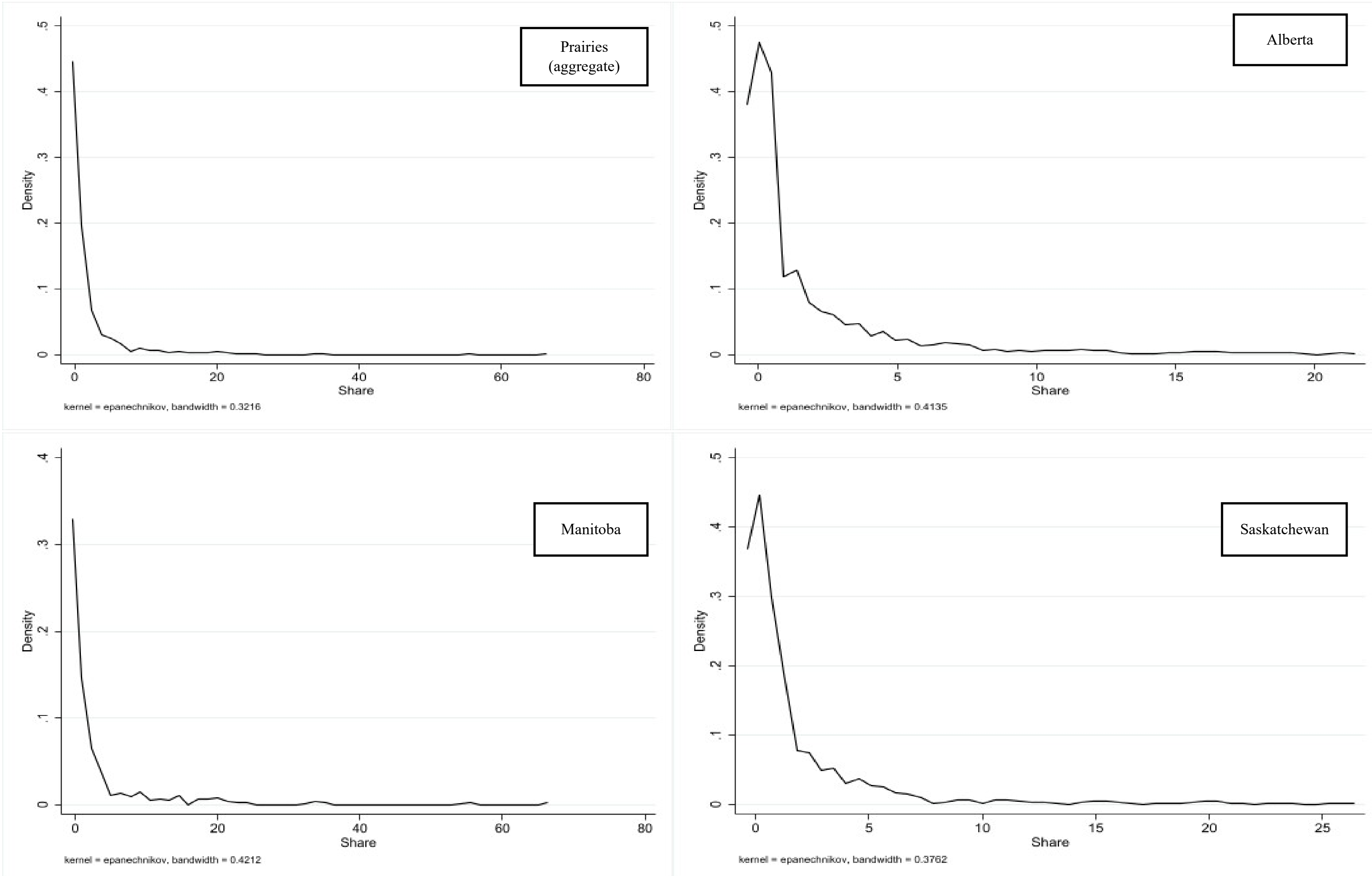


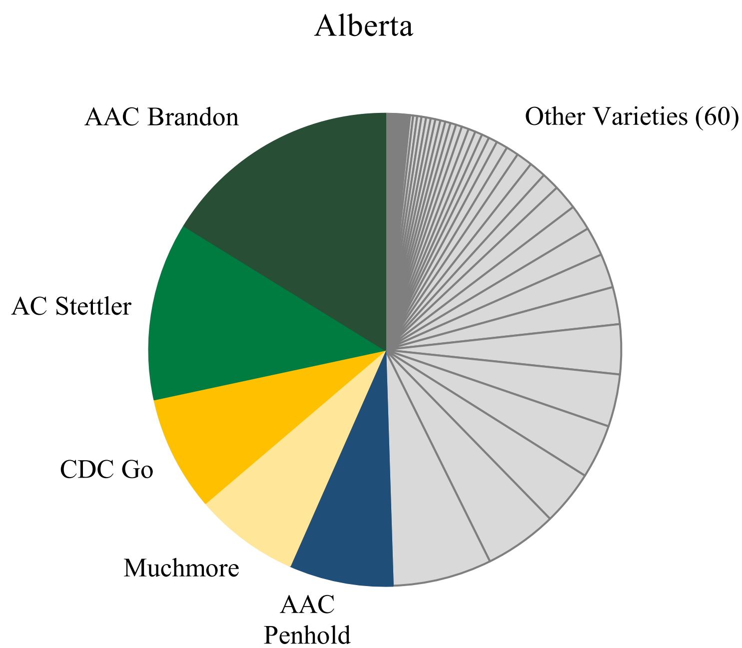
Figure 4.4(b): Adoption measured in share of provincial acres



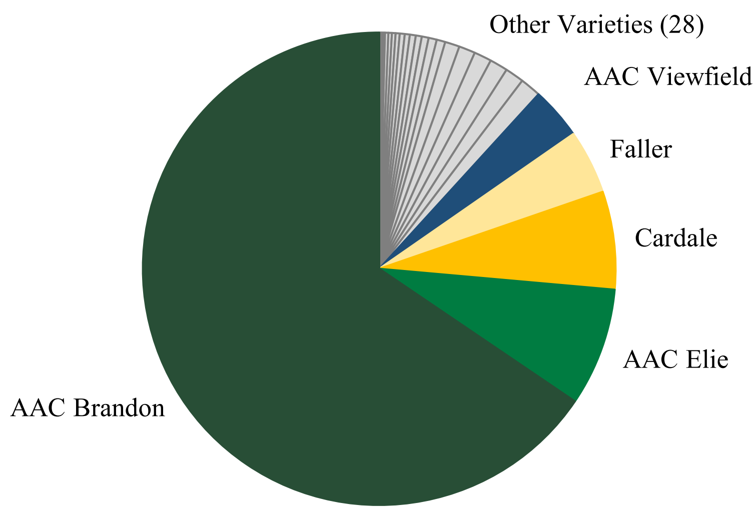
Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

Similar to Dahl et al.'s (1999) observation of a high concentration in few varieties of hard red spring wheat in the Canadian prairie provinces, the data appears to reveal a high concentration of wheat acreage in a small number of varieties. For example, in 2018, the five most popular varieties in each province account for at least 50% of total insured provincial wheat acreage that year (Figure 4.5). Of note is AAC Brandon, the top variety by 2018 across the Prairies, which accounts for over 65% of Manitoba's total acreage. In this same year, approximately 120 varieties were registered for use in Manitoba, with 33 considered available, leaving the remaining 35% of acres allocated across 32 other varieties. This phenomenon is not limited to 2018. As Figure 4.6 reveals, the preceding five years exhibit similar concentrations of acreage in a handful of varieties, although which varieties form the top five does vary across years.

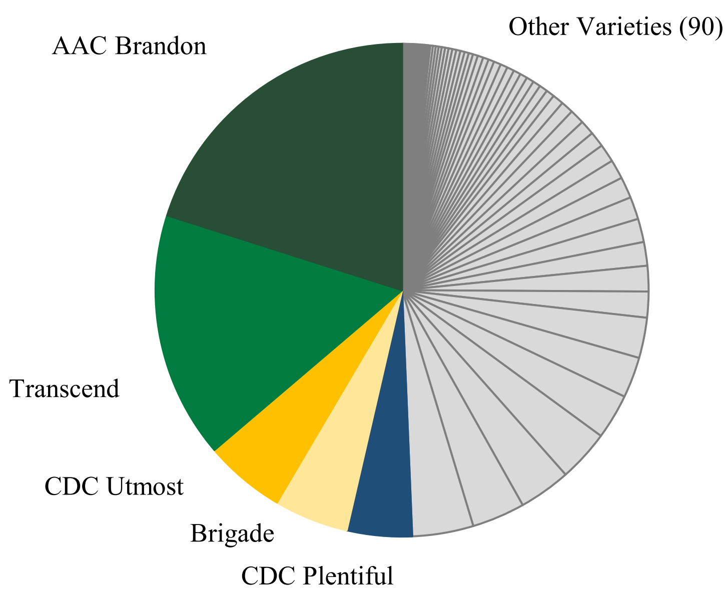
Figure 4.5: Provincial distribution of acres across five most popular varieties (2018)



Manitoba

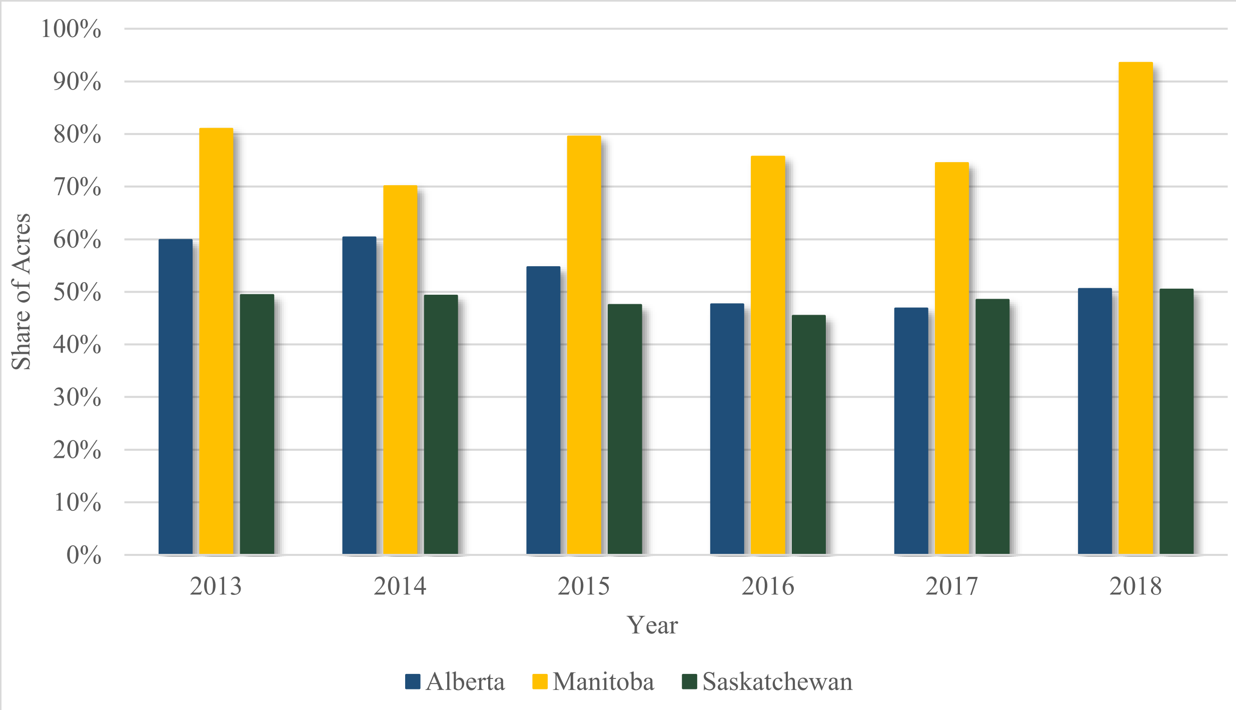


Saskatchewan



Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

Figure 4.6: Provincial market share of the top five wheat varieties by acreage each year (2013-2018)



Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

4.5 Data collection challenges

In this section, I discuss several of the challenges of the data collection process. These include some of the obstacles to aggregating the data, which I briefly discussed in section 4.3. I expand on these challenges further and point to possible causes for such issues, in addition to indicating the representativeness of the dataset and any further limitations to consider.

4.5.1 Obstacles to aggregating the data

The process of obtaining the data for this study took over 15 months. Once acquired, inconsistencies in reporting formats of the raw datasets required some transformation of the data. As I previously mention in this chapter, reporting of several varietal traits vary between provinces, and in some cases within a province. This is true for both Manitoba's variety heights and protein contents. In the case of variety heights, the first two years of data (i.e., 2009-2010) record height as semi-dwarf, medium, medium-tall, or tall and in centimetres relative to the check variety in the following years. Confirming with a contact for Manitoba that only the reporting format changed between 2010 and 2011, not the actual nature of measurement (Kirk, 2020a), I convert both the ratings for 2009-2010 and the reported heights for 2011-2018 to a four-point scale. The breakdown of quartiles for converting heights from inches to a four-point scale is the same one used to similarly transform heights for Alberta and Saskatchewan in section 4.3.2, where 1 is indicative of shorter varieties. A similar issue occurs with Manitoba's protein measurement, although in this case it simply shifts from reporting percentage relative to the check variety from 2009-2012 to reporting the actual protein percentage in the remaining years. To correct this, I use reported protein percentages for the check varieties from 2009-2012 to determine the actual percentages for all varieties.

CNHR varieties Faller, Elgin ND, and Prosper present their own challenges. All three varieties are grown in Manitoba and Saskatchewan over the time period of concern. However, yield publications report on these varieties prior to their registration dates as CNHR in 2018, some as early as 2010. This complicates the age determination as Seed Guides do not report on these varieties until 2016, where they are initially classed as CWIW. According to the CFIA, protective direction was granted for Faller in 2008, Prosper in 2012, and Elgin ND in 2014 (Canadian Food Inspection Agency, 2020). As a result, I use these dates to determine ages of these three varieties. Although using the date of protective direction granting fails to fully represent the length of time that these varieties have been available, it does provide an approximate age.

Additionally, Faller, Elgin ND, and Prosper yields are only available in metric (tonnes/acre) in Manitoba for 2014 through 2017. Using a ratio of 36.744 bu/tonne of wheat (Manitoba Agriculture Statistics, n.d.), I converted these yields to the imperial measure (bu/acre). The reason for this discrepancy is unclear, as reported yields for other varieties during these use imperial units.

Another obstacle in dataset construction is the discrepancies between Yield Magazine and Seed Guide reported varieties. In several cases, a variety listed in the Yield Magazine for a particular year is not included in the corresponding Seed Guide. The reverse scenario is also prevalent which results in a subset of corresponding data between the two provincial publications. According to industry experts, this issue appears to stem at least in part from the registration system. For a variety to be registered, it must have three years of official trial data, conducted by a recognized organization (Agriculture and Agri-Food Canada, 2013b). Under this system, a variety may be registered without going through provincial trials (Kirk, 2020a). For example, AAFC or private trials may collect the trait data, leaving it unreported in the provincial Seed Guide (Kirk, 2020a). However, Yield Magazines still list data for all varieties planted on insured acres in a given year. This allows varieties to appear in the provincial Yield Magazine even though the Seed Guide for that year did not report on them (Kirk, 2020a). In the opposite scenario, it may be that the distributor has not yet picked up a variety listed in the Seed Guide, resulting in no yield reports for that year (Kirk, 2020a). The combination of these two scenarios leaves a subset of data containing both non-yield agronomic characteristics and yield performance for a variety.

Reporting format differences across provinces complicated aggregating the three provincial datasets into a single dataset for the Canadian Prairies. Section 4.3.2 provides a discussion of the process for addressing these issues. However, consistent measurements across provinces for variety seed weight and test weight variables are not possible, meaning that these variables are only used in provincial level modeling. This is due to differences in reporting formats between provinces, with no data available for test weights and insufficient information regarding how the four-point scale used to measure variety seed size is determined in Manitoba.

4.5.2 Missing data

Another challenge in the data collection process is missing data. Yields are not reported by crop insurance corporations for varieties below a minimum threshold. In Saskatchewan, this threshold is a minimum allocation of 400 acres to the variety withing a risk zone. Similarly, Manitoba reports yields only when at least 500 acres of the variety is grown in a rural municipality, and Alberta requires a minimum of 5 producers of the variety within a risk zone. As a result, the datasets do not contain complete information on insured acres. In order to identify the representativeness of the data, I obtained total acreage of each wheat class from the Canadian Grain Commission, the Agriculture Financial Services Corporation, and the Manitoba Agricultural Services Corporation. From this, I determined the relative share of missing data for each wheat class in each province. This information is presented in Table 4.4. The largest wheat class, hard red spring (HRS), is missing less than 8% of its total acres in Manitoba and only 4.6% in Alberta. However, Saskatchewan's rate of missing data is relatively high for this class, at 27.5%. Consequently, the empirical analyses in this thesis are conducted with strong confidence for HRS wheat in Alberta and Manitoba, but caution is necessary when interpreting modeling results for Saskatchewan. Additional care is needed when interpreting modeling results for most other classes due to their relatively higher rates of missing information.

In addition to a summary of the rates of missing information, Table 4.4 provides important information regarding the definition of wheat classes. While official wheat classes are determined by the Canadian Grain Commission, each provincial publication has small differences in how they refer to these classes. To simplify this, I aggregate wheat classes into seven groups: hard red spring (HRS), Canada prairie spring (CPS), durum, extra strong (ES), hard white spring (HWS), Khorasan, and winter. The second, third, and fourth columns of Table 4.4 show which classes from each publication fall into each of these seven larger classes. Moving forward, wheat class refers to these larger groups found in column two.

Table 4.4: Overview of missing data in various wheat classes based on yield data available

Province	Wheat classes (Thesis)	(Yield Magazine)	(Seed Guide)	Average percentage of insured harvested acres without yield and acreage data	Share of class in total area (%)	Weighted average of missing data across all classes (%)
Alberta 2013-2018	HRS	HRS	CWHWS, CWRS,	4.61	72.90	5.47
	CPS	CPS	CPSR, CWGP, CWSP, CPSW	9.16	12.46	
		SWS	CWSWS	8.84	2.64	
	Winter	HRW	CWRW	28.37	1.12	
	Durum	DURUM		3.23	10.70	
	CNHR	CNHR**		38.33	0.18	
Manitoba 2009-2018	HRS	RS	CWRS	7.40	80.85	9.51
	HWS	HWS	CWHWS	29.34	0.66	
	CNHR	NHR	CNHR	14.29	7.73	
	ES	ES	CWES	75.00	0.06	
	CPS	OS	CWSWS, CWGP	38.12	2.09	
		PS	CPSR, CPSW	32.19	0.83	
	Durum	DURUM		52.63	0.07	
	Winter	Winter		14.09	7.70	
Saskatchewan 2009-2018	CPS	CPSW	CPSR, CPSW, CWGP, CWSP, CWSWS	53.70	5.76	31.23
	ES	ESRSW	CWES	no total acres available	-	
	Durum	Durum		31.79	34.20	
	HRS	HRSW	CNHR, CWRS	27.47	58.03	
	HWS	HWSW	CWHWS	64.44	0.23	
	Khorasan	Khorasan		no total acres available	-	
	Winter	Winter		66.03	1.78	

Sources: Canadian Grain Commission (n.d.a), Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.).

A final issue is the unavailability of Seed Guide data for Alberta prior to 2013. The lack of available data for 2009-2012 reduces the scope of Alberta's analyses by four years, relative to the other two provinces. However, the number of available observations is still comparable to Manitoba's, and the rates of missing yield data are relatively low for the years that trait data is available.

4.5.3 Summary of data collection challenges

In short, unavailable and inconsistent data reporting are the greatest challenges of data collection. The length of time that it took to obtain the necessary data is a key indicator of these issues. From a producer perspective, such challenges could create information asymmetries that negatively impact their ability to maximize profits. As a researcher, these challenges may reduce the generalizability of my results. However, aggregating this data into a dataset containing all three Prairie provinces improves on the overall number of observations, allowing me to capture an overall idea of which varietal traits factor into variety decisions most within the context of available data.

Chapter 5: Empirical model

5.1 Introduction

Chapter five outlines the empirical approach of this thesis. The first section provides a short overview of some of the empirical approaches to modeling agricultural technology adoption in the literature. The next section discusses several viable empirical models based on the approaches of this existing literature and current panel data econometric techniques. Following this are sections describing the dependent and independent variables. Finally, I present the specification of the econometric model and associated estimation procedures.

5.2 Empirical modeling approaches in the literature

Empirical analysis of technology adoption behaviour relies on the conceptual frameworks outlined in section 3.2 to quantify the effects of various factors of adoption. Using this empirical approach, the effects of specific factors in the decision process can be used to understand current conditions and predict the success of new technologies in the future. These analyses conducted are either ex-ante or ex-post.

Ex-ante empirical studies aim to predict market acceptance of a new technology prior to its release (Weersink & Fulton, 2020). One approach in this setting is the use of choice experiments to estimate farmers' willingness to pay (WTP). This type of approach to empirical modeling of agricultural technology adoption is most helpful for products not yet available or in the absence of well-functioning markets for the technology (Asrat et al., 2010). Considering sorghum and teff variety adoption in Ethiopia, Asrat et al. (2010) elicit farmers' WTP for various attributes of each variety. Farmers were asked to choose one of three varieties of either sorghum or teff based on the productivity, value, environmental adaptability, and yield stability of the variety. Using a random parameters logit model to examine responses, Asrat et al. (2010) find that farmers are willing to forego some income in favour of more stable yields and better environmental adaptability.

Ex-post empirical studies rely on the availability of economic data and examine revealed preferences for new technology based on the current behaviours of agriculture producers. In general, ex-post approaches employ one of the conceptual frameworks, outlined in chapter three, as a guideline (Weersink & Fulton, 2020). Both individual farm and aggregate adoption behaviours can be examined in these empirical studies, depending on the nature of the data.

Where either panel or cross-sectional data is available, analysis is focused on individual farm adoption behaviour (Weersink & Fulton, 2020). This approach is used in several studies (Barkley & Porter, 1996; Dahl et al., 1999; Fernandez-Cornejo & McBride, 2002; Barret et al., 2004; Dahl et al., 2004; Abadi Ghadim et al., 2005; Coromaldi et al., 2015), in part because cross-sectional and panel data are often more readily available. Using cross-sectional data, Coromaldi et al. (2015) apply an endogenous switching regression model to understand which factors affect uptake of modern varieties in Uganda and Barkley and Porter (1996) use two-stage weighted least squares in their study of Kansas wheat adoption.

Dahl et al. (1999), Fernandez-Cornejo and McBride (2002), and Abadi Ghadim et al. (2005) employ Tobit models to for their empirical analyses. The Tobit model is often used in cross-sectional and panel data adoption studies where the dependent variable is constrained or the data is truncated. Further, unlike binary adoption modeling, Tobit models estimate both the likelihood and the extent of adoption (Fernandez-Cornejo & McBride, 2002; Abadi Ghadim et al., 2005). Given that for many agricultural technologies, the decisions to adopt and the intensity of this adoption are simultaneous (Fernandez-Cornejo & McBride, 2002), this empirical approach provides additional relevant information not captured in other models. Dahl et al. (1999) employ a Tobit model in their study of wheat adoption, using the input characteristic model previously described for specification of the empirical model. However, they also consider a pooled linear approach to empirically estimating adoption of HRS wheat using the same specification (Dahl et al., 1999).

Empirical analyses using time-series data concern aggregate adoption behaviour and the diffusion path (Weersink & Fulton, 2020). These studies are generally concerned with predicting and explaining diffusion paths. For example, Kuehne et al. (2017) develop an adoption and diffusion outcome prediction tool (ADOPT) to predict the level of and the time to peak adoption of agricultural technology. ADOPT relies on factors of adoption which indicate the relative advantages and the ease of learning associated with the new technology (Kuehne et al., 2017). Testing ADOPT’s ability to accurately predict aggregate adoption levels and speed, Kuehne et al. (2017) find that for Mace wheat in Western Australia, ADOPT estimations of both the predicted level and predicted timeline for peak adoption are reasonably close to actual observations. Other studies in the literature of aggregate adoption behaviour for agricultural technology use random effects models when dealing with panel data (Fischer et al., 1996) or logistic estimation (Dinar & Yaron, 1992) to predict diffusion paths over time.

While the above review summarizes many of the approaches of the existing literature in crop adoption, many of these empirical models are not capable of accounting for unobservable variety specific time invariant effects while simultaneously providing estimates for observable time invariant variety traits. This is an issue in the case of wheat variety adoption, where both time invariant traits and variety specific effects are included in the adoption model. Most existing approaches in the agricultural literature have relied on pooling panel data in order to be able to identify effects for time invariant varietal traits (Barkley & Porter, 1996; Dahl et al., 1999). However, in neglecting to address the panel nature of the data the resulting estimates are likely biased and inconsistent (Baltagi, 2005; Verbeek, 2017).

In the following section, I explore some of these empirical approaches and the advantages and disadvantages of each in more detail. Additionally, I consider several other empirical models that were not used by this subsample of the literature but may have desirable empirical properties for this application.

5.3 Research aims and empirical models

The key aim of this study is to determine which varietal attribute(s) are most important to variety adoption decisions by wheat producers on the Canadian prairies. Of particular interest is the relationship between a variety's adaptability to various growing conditions and its adoption. I explore these relationships empirically for overall variety adoption, as well as for particular wheat classes and provinces using several econometric models.

The dependent variable in the adoption models takes two forms: first as the total insured acreage, and second as the percentage share of total insured acres. Therefore, I consider both least squares and maximum likelihood based econometric models. Further, the empirical models deal with three types of independent variables: time variant, slowly changing, and time invariant.

Time variant independent variables such as average yield, and the degree of specificity change over time for each variety. Slowly changing, or rarely changing variables exhibit minimal within-group (i.e., within-variety) variation from year to year (Breusch et al., 2011; Greene, 2011). Some examples are variety disease tolerance, maturity rate, and height, which change slowly across years either due to changes in the provincial rating scale or as knowledge about a particular variety improves (Kirk, 2020b). Finally, time invariant attributes remain constant over the time period (e.g., head awn), the variety either has the trait or it does not.

The following sections present the relevant empirical models and their respective advantages and disadvantages in modeling wheat variety adoption. This includes the abilities of these econometric models to deal with the various types of dependent and independent variables. Table 5.1 in the final section provides a brief summary of the key elements of each approach.

5.3.1 Pooled ordinary least squares

The first model, the pooled ordinary least squares (pooled OLS) regression model, is specified as follows:

$$y_{it} = \alpha + x_{it}\beta + z_i\eta + \varepsilon_{it} , \tag{5.1}$$

where α is the constant, $i = 1, \ldots, n$ varieties and $t = 1, \ldots, T$ time periods. Here y_{it} represents the adoption level measured in acres, x_{it} represents the set of time variant and slowly changing independent variables and z_i is the set of observed time invariant regressors. β and η are the parameters of interest to be estimated and ε_{it} is the error term. Alternatively, Equation (5.1) is written as:

$$y = X\beta + Z\eta + \varepsilon , \tag{5.2}$$

where y and ε are $nT \times 1$ vectors, X is a $nT \times K$ matrix, Z is a $nT \times G$, β is a $K \times 1$ vector, and η is a $G \times 1$ vector. The pooled OLS estimators of β and η are:

$$\hat{\beta}_{POLS} = (X'X)^{-1}X'y , \tag{5.3}$$

$$\hat{\eta}_{POLS} = (Z'Z)^{-1}Z'y\,, \tag{5.4}$$

where $\hat{\beta}_{POLS}$ is a $K \times 1$ vector and $\hat{\eta}_{POLS}$ is a $G \times 1$ vector. Under the Gauss-Markov assumptions, $\hat{\beta}_{POLS}$ and $\hat{\eta}_{POLS}$ are best linear unbiased estimators (BLUE) (Verbeek, 2017).[24]

This straightforward approach examines the relationship between adoption (measured as total insured acreage) and both time variant and time invariant variety characteristics. However, pooled OLS ignores the panel nature of the data, instead stacking it and estimating using OLS. If there is minimal variation within a panel across years, this approach may be more efficient than a fixed effects approach (Verbeek, 2017). But, where sufficient heterogeneity between panels exists, pooled OLS produces biased and inconsistent estimators (Baltagi, 2005; Verbeek, 2017). Given that the registration process requires differentiation between new and existing varieties, I expect biased pooled OLS estimates (Canadian Food Inspection Agency, 2012). In this case, a panel data econometric approach is more appropriate.

5.3.2 Fixed effects

The fixed effects regression is one panel data econometric approach. With a specific set of *n* varieties, this model captures unobserved heterogeneity and time invariant factors by allowing the variety specific coefficients to vary across varieties (Baltagi, 2005; Verbeek, 2017). To do this, the standard fixed effects model uses a one-way error component with a single cross section variable, in this context the variety, to measure changes within a variety over time (Baltagi, 2005; Verbeek, 2017). A more complex fixed effects model is the two-way error component model which captures both time fixed effects and variety fixed effects (Baltagi, 2005). This alternative model and its appropriateness for modeling variety adoption is discussed in more detail in Appendix C with results included in Appendix D.[25] Key to both of these models is the

[24] The Gauss Markov assumptions are: (1) y_{it} is linear in parameters (2) $E(\varepsilon_{it}) = 0$ (3) Homoskedasticity: $v(\varepsilon_{it}) = \delta^2$ (4) No autocorrelation: $Cov(\varepsilon_{it}, \varepsilon_{is}) = 0$ (5) No endogeneity: $Cov(\varepsilon_{it}, x_{it}) = 0$ (6) x_{it} and z_i are non-stochastic (7) $\varepsilon_{it} \sim N(0, \sigma^2)$.

[25] The two-way fixed effects model is not included in the main analysis due to a combination of unclear interpretations of the results in this context and a lack of severe shocks or visible trends in total insured and seeded acreages at either the provincial or prairie-wide levels. Further details on this are available in Appendix C, with results for a two-way fixed effects model included in the tables of alternative models in Appendix D.

allowance of endogeneity between *all* regressors and the variety specific fixed effects (Baltagi et al., 2003; Baltagi, 2005; Verbeek, 2017).

Using the least squares dummy variable estimator (LSDV), which adds a dummy variable for each variety into the model, the fixed effects equation is:

$$y_{it} = \alpha + x_{it}\beta + \varepsilon_{it} , \quad (5.5)$$

where, following Baltagi's (2005) definition, the one-way error component ε_{it} is specified as:

$$\varepsilon_{it} = d_i\gamma + w_{it} . \quad (5.6)$$

Here, d_i denotes variety dummy variables, γ represents the variety specific fixed effects, and w_{it} is the stochastic error component. The z_i's from Equation (5.1) in this case are a linear combination of the dummy variables; therefore η cannot be separated from γ. However, when the number of varieties *n* is large, the LSDV approach requires too many individual dummy variables (Baltagi, 2005; Verbeek, 2017).

Alternatively, the within estimator is identical to the LSDV, but uses a regression model in deviations from variety means (Baltagi, 2005; Verbeek, 2017). Subtracting the variety means from Equation (5.5), the within transformed model is:

$$\tilde{y}_{it} = \tilde{x}_{it}\,\beta + \widetilde{w}_{it} , \quad (5.7)$$

where $\tilde{y}_{it} = y_{it} - \frac{\sum_{t=1}^{T} y_{it}}{T}$, $\tilde{x}_{it} = x_{it} - \frac{\sum_{t=1}^{T} x_{it}}{T}$, and $\widetilde{w}_{it} = w_{it} - \frac{\sum_{t=1}^{T} w_{it}}{T}$. The time invariant fixed effects cancel out in this step. Rewriting this in matrix form, the model is:

$$\tilde{y} = \tilde{X}\beta + \widetilde{W}, \quad (5.8)$$

where $\tilde{y}$ and $\widetilde{W}$ are $nT \times 1$ matrices, $\tilde{X}$ is $nT \times K$, and β is $K \times 1$. The fixed effects estimator of β is:

$$\hat{\beta}_{FE} = \left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}'\tilde{y} . \quad (5.9)$$

Here, $\hat{\beta}_{FE}$ is a $K \times 1$ vector. Assuming that all x_{it} are independent of all w_{it}, the fixed effects estimator $\hat{\beta}_{FE}$ is unbiased (Verbeek, 2017).

Advantages of the fixed effects approach are that it produces a consistent estimator and allows us to address variety specific omitted variable bias by focusing on within-variety variations (Verbeek, 2017). However, no coefficients on the observable time invariant attributes are generated using this method. As one of the aims of empirical modeling includes determining the coefficients on time invariant variety attributes such as head awn, this approach will not be sufficient to answer all of the research questions.

5.3.3 Random effects

To capture time invariant attribute effects, one alternative is the random effects regression model. This model estimates the time invariant variable effects while accounting for the panel nature of the data within a single regression using generalized least squares estimation (Baltagi, 2005). Combining Equation (5.1) and Equation (5.6), the random effects model is:

$$y_{it} = \alpha + x_{it}\beta + z_i\eta + d_i\gamma + w_{it}\,, \tag{5.10}$$

where all variables are as previously defined. This random effects model is better than the fixed effects in that it provides estimates for the time invariant variety traits. However, in contrast to the fixed effects model which allows correlation between the independent variables and the variety specific effects, the random effects approach assumes that *all* independent variables are exogenous, meaning that there is no correlation between the variety specific effect γ and all independent variables (i.e., x_{it} and z_i) (Baltagi et al., 2003; Baltagi, 2005; Verbeek, 2017). This key assumption of the random effects models does not hold for variety adoption, as at least some of the explanatory variables (i.e., yield potential) are impacted by unobservable variety specific traits. Therefore, this approach is not appropriate for this thesis.

5.3.4 Hausman-Taylor instrumental variable

Alternatively, I consider the Hausman-Taylor instrumental variable (Hausman-Taylor IV) model. Developed to address the limitations of the fixed effects and random effects models, the Hausman-Taylor IV model allows *some* regressors to be correlated with the variety specific effects, alleviating the restrictive *all or nothing* assumptions of the other two models (Baltagi et al., 2003; Baltagi, 2005). This alternative approach splits the independent variables into exogenous and endogenous groups and uses the within and between variation of the strictly exogenous variables as internal instruments for the endogenous variables (Baltagi et al., 2003; Baltagi, 2005).

The Hausman-Taylor model is:

$$y_{it} = \alpha + x_{1it}\beta + x_{2it}\beta + z_{1i}\eta + z_{2i}\eta + d_i\gamma + w_{it}\,, \tag{5.11}$$

where the x_{1it} and z_{1i} regressors are exogenous to the variety specific effects γ by assumption. Conversely, x_{2it} and z_{2i} are endogenous regressors. As in the other models, x_{1it} and x_{2it} represent the time variant regressors, while z_{1i} and z_{2i} indicate the time invariant regressors. An alternative representation of Equation (5.11) is:

$$y = X\beta + Z\eta + D\gamma + W\,. \tag{5.12}$$

Here, $X = [X_1, X_2]$ is a $nT \times K$ matrix where X_1 is a $nT \times k_1$ vector of the x_{1it}, X_2 is a $nT \times k_2$ vector of the x_{2it}, and $K = k_1 + k_2$. Similarly, $Z = [Z_1, Z_2]$ is $nT \times G$ matrix where Z_1 is a $nT \times g_1$ vector of the z_{1i}, Z_2 is an $nT \times g_2$ vector of the z_{2i}, and $G = g_1 + g_2$. Finally, D is a $nT \times n$ matrix of variety dummy variables, γ is a $n \times 1$ vector, and W is a $nT \times 1$ vector of the random error component. Pre-multiplying by the variance covariance $\Omega^{-\frac{1}{2}}$ matrix of the error term $d_i\gamma + w_{it}$, the Hausman-Taylor model performs a two-stage least squares estimation using $A = [\tilde{X}, \bar{X}_1, Z_1]$ as the instrumental variables (Baltagi et al, 2003; Baltagi, 2005). Here, $\tilde{X}$ is the within transformation of X and $\bar{X}_1$ is the time averages of X_1. The Hausman-Taylor estimators of β and η are:

$$\hat{\beta}_{HT} = \left(\breve{X}' P_A \breve{X}\right)^{-1} \breve{X}' P_A \breve{y}\,, \tag{5.13}$$

$$\hat{\eta}_{HT} = \left(\breve{Z}' P_A \breve{Z}\right)^{-1} \breve{Z}' P_A \breve{y}\,, \tag{5.14}$$

where P_A is the projection matrix of $A = [\tilde{X}, \bar{X}_1, Z_1]$ and $\breve{X}, \breve{Z}$, and $\breve{y}$ are generalized least squares transformations (Baltagi, 2005).

In theory, this approach addresses some of the weaknesses of the pooled OLS, fixed effects, and random effects models. First, it accounts for heterogeneity between varieties, reducing the risk of bias inherent with a pooled OLS approach. Second, this approach has the added advantage over the standard fixed effects model of allowing us to estimate the coefficients on the observed time invariant regressors. Third, as long as there are more exogenous time variant regressors than endogenous time invariant regressors (i.e., $k_1 > g_2$), the Hausman-Taylor IV model is more efficient than the standard fixed effects model (Baltagi et al., 2003; Baltagi, 2005). Finally, this approach relaxes the restrictive exogeneity assumption of the random effects model (Baltagi et al., 2003; Baltagi, 2005).

In practice, the additional assumptions of the Hausman-Taylor IV model are potentially problematic. Due to the model's use of exogenous variables as internal instruments for the endogenous variables, this model requires knowledge of which variables are uncorrelated with the variety specific effects. However, in the absence of a pretest for this exogeneity, identifying viable internal instruments with certainty is difficult, if not impossible, in empirical applications. As Chatelain and Ralf (2021) explain, "without a pretest for the exogeneity of internal instruments, the Hausman-Taylor estimator faces potential endogeneity bias by wrongly assuming that all internal instruments are exogenous" (p.157).

In the context of wheat variety adoption, this endogeneity bias is a likely issue. While confidence in the exogeneity of variety head awn is fairly strong, for several other variety attributes, the argument for exogeneity is less obvious. For example, in this thesis, I argue that variety disease tolerance is intrinsic to the variety and that including varietal adaptability explicitly in the model removes any possible correlation between disease tolerance and the variety specific effects that stem from growing condition sensitivity. However, there is a degree of doubt in this argument. This challenge of confidently identifying exogenous variables, paired with a limited number of time variant independent variables, most of which are likely correlated with the variety effects, indicates the Hausman-Taylor IV model is not the best approach for this thesis.

5.3.5 Fixed effects filter

A third alternative to the fixed effects model is the fixed effects filter (FEF) model. Developed by Pesaran and Zhou (2018), this relatively newer approach builds on the standard fixed effects model by allowing for the estimation of effects for time invariant variety traits and involves two steps:

Step (1): Estimate the standard fixed effects model containing all time variant regressors on the level of adoption using Equation (5.5) and Equation (5.6).

Step (2): Estimate the effects of the observable time invariant regressors on the time averages of the residuals obtained in the first step $\bar{u}_i$ using OLS. This secondary regression is specified as:

$$\bar{u}_i = \rho + z_i'\eta + \delta_i \,, \tag{5.15}$$

where $\bar{u}_i = \frac{\sum_{t=1}^{T}(\tilde{y}_{it} - \tilde{x}_{it}'\hat{\beta}_{FE})}{T}$, ρ is the constant, δ_i represents the error term of this second regression, z_i is the set of observed time invariant regressors and η the FEF estimated effects of these variables. In matrix form, the FEF estimator for β is $\hat{\beta}_{FEF} = \hat{\beta}_{FE}$ and for η is:

$$\hat{\eta}_{FEF} = (Z'Z)^{-1}Z'\bar{u} \,, \tag{5.16}$$

where $\bar{u}$ is a $nT \times 1$ matrix of the time averaged residuals in Step (1). The first step of the FEF filters out the effects of the time variant regressors, allowing the second step to provide estimated coefficients for the observed time invariant traits (Law & Zhou, 2017; Pesaran & Zhou, 2018). Conditioning on the orthogonality of the observed time invariant traits and the variety specific fixed effects (i.e., $cov(z_i, \delta_i) = 0$), Pesaran and Zhou (2018) show that this FEF estimator is consistent, even in the presence of residual serial correlation.

Although its relative newness means that Pesaran and Zhou's (2018) FEF approach is not as widely used in the agricultural technology adoption literature as some of the other models previously discussed, this model has several advantages. First, the FEF includes variety specific effects, accounting for the variety specific heterogeneity ignored by a pooled OLS approach. In the context of wheat adoption, this is important, as by nature of the variety registration system, wheat varieties are inherently differentiated (Canadian Food Inspection Agency, 2012). Second, the FEF model utilizes the well-established fixed effects model but adds the ability to provide estimated coefficients for time invariant variables. Third, it does not require the critical assumption of the random effects model that there is no correlation between regressors and variety specific effects which, as discussed above, cannot be met in the context of this thesis. Fourth, the FEF approach conditions only on orthogonality between the time invariant variables and variety specific effects. This is advantageous to the Hausman-Taylor IV which requires assumptions regarding the orthogonality of all variables and these variety effects; assumptions that come with limited confidence for wheat variety traits. Further, because the first step of the FEF is a fixed effect model, only the second step estimates are impacted if the orthogonality assumptions are incorrect. This is preferable to the Hausman-Taylor IV model, where all estimates suffer from bias when one of its many assumptions fail (Chatelain and Ralf, 2021). Finally, the FEF model has the same respective advantages over the Tobit and fixed effects Tobit models discussed in the next section as it does over the pooled OLS and fixed effects approaches.

Overall, the FEF model addresses variety specific heterogeneity, while providing estimates for all independent variable types with minimal exogeneity assumptions. In aggregate, these advantages suggest that this approach is the most appropriate for empirically modeling wheat variety adoption decisions in this thesis. However, this approach is not possible when the dependent variable takes the form of the percentage share of total acreage.

5.3.6 Tobit and fixed effects Tobit

In the models where I treat the adoption dependent variable as the percentage share of total acreage, I consider the two-limit Tobit model where the dependent variable is constrained between 0% and the highest provincial market share achieved (Baltagi, 2005; Verbeek, 2017).

Analysis with this alternative dependent variable provides a robustness test of the results in the other models previously discussed and the Tobit approach avoids impossible predictions given the limited nature of this dependent variable (i.e., percentage by definition must be between 0 and 100). The model is:

$$y_{it}^* = \alpha + x_{it}\beta + z_i\eta + \varepsilon_{it} , \tag{5.17}$$

where

$$y_{it} = \begin{cases} y_{it}^* \; if \; 0 < y_{it}^* < h \\ 0 \; if \; y_{it}^* \leq 0 \\ 0 \; if \; y_{it}^* \geq h \end{cases} \tag{5.18}$$

and y_{it}^* denotes the latent dependent variable, measured as the percentage share of acres and h is the highest provincial market share achieved. All other variables are as previously defined in the pooled OLS model. The estimated marginal effects are:

$$ME_X^T = \beta_{\mathrm{T}}\Phi(\frac{x_{it}\beta_T}{\sigma}) , \tag{5.19}$$

$$ME_Z^T = \eta_{\mathrm{T}}\Phi(\frac{z_i\eta_T}{\sigma}) , \tag{5.20}$$

where x_{it} are again the time variant regressors, z_i are the time invariant regressors, β_T and η_{T} are the parameters from the Tobit model, Φ is the cumulative density function, and σ is the standard deviations of the residuals.

This model is well established as an approach to dealing with continuous limited dependent variables, using maximum likelihood to generate estimates (Baltagi, 2005; Verbeek, 2017). However, similar to the pooled OLS, the two-limit Tobit model ignores the panel nature of the data (Baltagi, 2005; Verbeek, 2017). If sufficient unobservable heterogeneity between varieties exists, then the estimates in this approach are biased (Baltagi, 2005).

An alternative is to use the fixed effects Tobit model. By including variety specific fixed effects γ in the model, it accounts for some of the omitted variable bias of the standard two-limit

Tobit (Baltagi, 2005). In this case, the error term is again split into Equation (5.6) with the estimated marginal effect:

$$ME_X^{FET} = \beta_{FET}\Phi(\frac{x_{it}\beta_{FET}}{\sigma}) , \tag{5.21}$$

Here, β_{FET} are the parameters from the fixed effects Tobit model, Φ is the cumulative density function, and σ is the standard deviations of the residuals for the fixed effects Tobit. However, this model is subject to finite sample bias in the estimated standard errors and does not provide estimated coefficients for time invariant traits (Greene, 2004a; Greene, 2004b). As these estimated standard errors are used to determine marginal effects, the fixed effects Tobit model is potentially biased.

5.3.7 Summary of models

The preceding discussion outlines the various advantages and disadvantages of seven regression models, summarized here in Table 5.1. From this discussion, it appears that Pesaran and Zhou's (2018) FEF model is the best fit for modeling wheat variety adoption. This model overcomes the shortcomings of each of the other six empirical models; allowing the estimation of both time variant and time invariant variety attribute effects without requiring as many challenging assumptions as the Hausman-Taylor IV model. Further it reduces the risk of bias, relative to the pooled OLS and Tobit models by accounting for variety differentiation. For these reasons, the preferred model is FEF model because it allows me to examine which varietal attribute(s) are most important in Western Canadian wheat producers' variety decisions. I include results from the other models for comparison purposes.

Table 5.1: Summary of key elements for relevant econometric approaches

Econometric Model	Limited dependent variable	Accounts for panel nature	Observable time invariant effects	Does not require assumptions regarding variety specific effects and:	
				Time variant regressors	Time invariant regressors
Pooled OLS			✓	✓	✓
Fixed effects		✓		✓	NA*
Random effects		✓	✓		
Hausman-Taylor IV		✓	✓		
Fixed effects filter		✓	✓	✓	
Tobit	✓		✓		
Fixed effect Tobit	✓	✓		✓	NA*

*These models do not include estimated effects for time invariant regressors.

5.4 Variables

This section outlines the variables of the empirical models. I present the two dependent variable forms first, followed by the time variant independent variables. Next, I discuss the time invariant and slowly changing independent variables. Finally, I provide the variable summary statistics for the prairie-wide (Table 5.3), provincial (Table 5.4), and wheat class (Table 5.5) levels.

5.4.1 Dependent variables

Following the approach of Torshizi (2015), the dependent variable takes two forms. I measure adoption as the insured acres (*acres*) that a given variety is grown on each year in the pooled OLS, Hausman-Taylor IV, and FEF models. For the two-limit Tobit and FE Tobit, I use the percentage share of provincial acres (*share*) to measure variety adoption. In this case, the dependent variable is constrained between 0% and the highest provincial market share achieved by a variety. However, the primary analysis of this thesis focuses on the FEF model due to its advantageous properties in this context, and therefore uses acres as the dependent variable in the discussions below.

5.4.2 Time variant independent variables

As defined earlier in this chapter, variety attributes which change over time for a particular variety are called time variant. Based on a review of the relevant literature, discussions with wheat industry members, and data availability in provincial publications, the degree of specificity, yield variance, yield potential, average yield, life cycle, and protein content form the set of time variant factors of wheat variety adoption for this thesis. Below is a short discussion of each of these variables.

The degree of specificity serves to indicate the sensitivity of a variety to its growing environment, which impacts varietal yields. Literature in this area of agricultural economics is limited, and much of the existing literature relies on yield variance to measure the impacts of yield uncertainty in crop adoption decisions (e.g., Barkley and Porter (1996)). However, as I previously discuss in chapter four, yield variance may be misleading. Therefore, I estimate varietal adaptability using the degree of specificity but include a second set of models with yield variance for comparison. From the conceptual framework developed in the previous chapter, I hypothesize that varieties with higher degrees of specificity will be less widely adopted. As this measure is the inverse of adaptability, it follows that I predict a positive relationship between variety adaptability and adoption.

Yield is another significant factor in adoption decisions, and as such, a majority of the crop adoption literature includes relative advantages in yield in some form (Barkley and Porter, 1996; Dahl et al., 1999; Abadi Ghadim et al., 2005; Asrat et al., 2010; Torshizi, 2015). Varieties with either higher average yield or superior yield potential offer an increase in expected profits for farmers. Therefore, I estimate the effects of both measures of yield on adoption in separate models, predicting that varieties with higher values of either yield measure have higher adoption rates.

Based on the existing literature, variety age is another determinant of adoption (Dahl et al., 1999; Torshizi, 2015). New varieties follow a cycle of initial growth in adoption, reaching a maximum market share, and then declining in use as newer varieties enter the market and older varieties become more susceptible to evolving diseases (Dahl et al., 1999). Therefore, I follow the approach of these studies, including variety age to the third-degree polynomial in the regressions, measured in months since release, to account for this pattern and allow for asymmetries in adoption and disadoption.

Protein content, the fourth time variant attribute, is a key determinant of both the wheat class of a variety and the quality grade wheat receives under the Canadian Grain Commission's grading standards (Canadian Grain Commission, n.d.b). Measured as the percentage content reported by each province and based on a long-term moving average (e.g., approximately 20 years in Manitoba), these values vary slightly from year to year (Kirk, 2020b). Such slight changes over time reflect the influences of growing and harvest conditions on realized protein, but are notably smaller than variations in the other time variant traits included in the dataset due to being a long-term moving average (i.e., the ratio of the standard deviation to mean is visibly smaller for protein content in the summary statistic tables available *Section 5.4.4*). Since the grade that a delivery of wheat receives within its wheat class influences the sale price, protein content serves as an end-use value indicator in this thesis. I anticipate that higher protein percentage varieties are more widely adopted.

5.4.3 Slowly changing and time invariant independent variables

As with the other explanatory variables outlined in this section, the slowly changing and time invariant factors of wheat adoption are based on the information available from the literature, industry, and provincial publications. Slow changing variety traits, as defined in section 5.3, vary slowly over time due to changes in the rating scale or improvements in knowledge about a particular variety (Kirk, 2020b). This means that these traits do not necessarily change in a tangible way (e.g., improved genetics), but do so as an artefact of grading on a relative scale leading to slight differences in their values across time. Depending on the scope of analysis (i.e., prairie-wide, provincial, wheat class), some of these traits are time invariant over the period of interest. [26] One variable, head awn, is time invariant at all analysis levels. Using the data available in the provincial Seed Guides, I consider the following additional determinants of wheat variety adoption.

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[26] Time invariant variables: head awn at all levels; all other slowly changing variables except for test weight become time invariant over the relevant time period in at least one of the subset models (see Appendix B for complete list).

The first is disease tolerance. Tolerance of wheat varieties to stem rust, leaf rust, stripe rust, loose smut, bunt, leaf spot, and fusarium head blight are reported in Seed Manitoba, Sask Seed, and the Alberta Seed Guide[27]. Table 5.2 provides an overview of the favourable conditions and impacts of disease outbreaks. Increased tolerance (i.e., higher tolerance ratings) to these diseases improve wheat quality and reduce the risk of loss to the producer, thereby increasing expected yields. As such, I expect each of these traits to impact variety selection. However, Alberta lacks sufficient available data for leaf rust and stem rust. To avoid omitting all observations for this province as a result of this incomplete information, I include leaf rust and stem rust only in provincial level modeling for Saskatchewan and Manitoba.

It also is important to clarify that when changes to disease tolerance ratings of a particular variety occur, it stems either from changes to the rating scale itself, or as more information is gathered on the variety and adjustments are made to its rating. In other words, the inherent disease tolerance (i.e., tolerance stemming from genetic design) does not change over time, but the perception of it may. Since farmer's variety decisions are based on the perceived disease tolerance published in Seed Guides, disease tolerances are time variant in some cases studied in this thesis.

[27] Alberta lacks sufficient available data for leaf rust and stem rust. To avoid omitting all observations for this province due to incomplete information within observations, leaf rust and stem rust are not included in modeling for prairie-wide, wheat class, and Alberta.

Table 5.2: Overview of favourable conditions and impacts of disease outbreaks

Disease	Conditions	Impacts
Stem rust	Favours excess moisture and moderate to high temperatures.	Early-stage infections can be severe, costing grain weight and quality.
Leaf rust	Favours moderate to high temperatures and excess moisture (rain or dew).	Negatively impacts kernels and test weights.
Stripe rust	Favours cooler temperatures and excess moisture.	Negatively impacts kernels and test weights.
Loose smut	Favour cooler, humid planting conditions.	Losses depend on affected spikes, with generally low incidence.
Bunt	Favours cooler temperatures at the germination stage.	Results in considerable yield loss for susceptible varieties.
Leaf spot	Favours a wide range of temperatures and long periods of excess moisture.	Severe cases reduce test weights by prematurely killing leaves.
Fusarium head blight	Favours humid conditions and moderate to high temperatures.	Negatively impacts grain quality. May also produce a harmful mycotoxin.

Source: Duveiller et al. (2012)

Sprouting resistance reduces the risk of lower grain quality that results from premature kernel germination prior to harvest (Mohan et al., 2009). This is more common under humid conditions, and results in a loss of starch content in end-use quality (Mohan et al., 2009) As sprouted wheat receives a lower grade by the Canadian Grain Commission, profits to farmers are reduced (Canadian Grain Commission, n.d.b). Therefore, I include sprouting tolerance as an explanatory variable in variety selection. As with variety disease tolerance, changes to the sprouting resistance rating over time reflect a change in relative perception, not in inherent resistance. As a result, changes within a variety are infrequent, making sprouting a slow changing variable.

Variety height and lodging tolerance are additional agronomic traits that impact the profitability of wheat. Lodging tolerance is a combination of plant height and the root and stalk structures keeping the plant upright, thereby protecting against associated yield losses (Kelbert et al., 2004). Semi-dwarf varieties are a common way to reduce susceptibility, as it is the taller wheat varieties that are most prone to lodging (Kelbert et al., 2004). However, semi-dwarf genes tend to result in lower protein content creating a trade off between the two traits (Kelbert et al., 2004). Given that both height and lodging tolerance influence variety profitability, I include them in the variety adoption model.

Wheat varieties with awned heads (bearded) are argued to be better protected against animals and have higher rates of photosynthesis, increasing the potential yield (Li et al., 2010; Bruening, 2019). As this is an advantage, I expect that varieties with awned heads will see higher rates of adoption. For this reason, I include a dummy variable indicating whether or not a variety has this trait.

As Barkley and Porter (1996) and Dahl et al. (1999) indicate, the expected days to maturity of a variety likely influences the adoption decision. Given the limited number of frost-free days across much of Western Canada, it is plausible that farmers prefer faster maturing varieties. Therefore, I anticipate a positive relationship between faster maturity rates and adoption.

Like protein, the test weight is a key determinant of the quality grade wheat receives under the Canadian Grain Commissions grading standards (Canadian Grain Commission, n.d.b). As these grades influence the price producers receive, the test weight is treated as an additional end-use value indicator where higher values are expected to increase adoption. Reported only for Alberta (lb/bu) and Saskatchewan (relative kg/hl), this variable is only included in the provincial level analyses.

Finally, I consider variety seed weight. A factor of seeding rates and therefore a factor in variety decisions, each province measures variety seed weight differently (Gray, 2021). Alberta reports this variable as the thousand kernel weight (TKW) in grams. Saskatchewan provides seed weight in milligrams relative to the check and Manitoba uses a four-point rating of seed size. Due to these differences in reporting, seed weight is only included in the provincial level models.

5.4.4 Summary statistics

This section presents the summary statistics at the prairie-wide, provincial, and wheat class levels for each variable. In the full prairie-wide dataset there are 1,230 potential observations available obtained from the CFIA's variety registration database, provincial Seed Guides, and Yield Magazines. Chapter four of this thesis provides a detailed discussion of the configuration and representativeness of this data. Of note, I omit leaf rust and stem rust tolerance from Alberta's summary statistics due to insufficient provincial data for these traits. Additionally, the prairie-wide and wheat class level analyses exclude these two variables as including them omits all observations for Alberta from the models.

Table 5.3: Prairie-wide level summary statistics

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	1,230	75,106.74	154,472.60
Share	%	1,230	2.01	4.72
Lag yield potential	bu/acre	945	56.91	13.65
Lag average yield	bu/acre	945	47.36	10.66
Lag variety specificity		824	3.23	2.58
Lag yield variance	bu/acre^2	824	81.86	93.58
Age	months	1,230	103.04	75.86
Age^2	months^2	1,230	16,365.90	23,761.88
Age^3	months^3	1,230	3,393,756.00	7,521,464.00
Protein	%	1,139	14.04	0.90
Stripe rust	scale 1-5	1,143	3.35	1.16
Loose smut	scale 1-5	1,216	3.00	1.17
Bunt	scale 1-5	1,227	3.50	1.36
Leaf spot	scale 1-5	1,206	2.41	0.67
Fusarium head blight	scale 1-5	1,225	2.31	1.01
Sprouting	scale 1-5	1,133	3.30	0.94
Lodging	scale 1-5	1,230	3.88	0.81
Height	scale 1-4	1,230	2.67	0.59
Head awn	dummy variable	1,103	0.62	0.48
Maturity rate	scale 1-5	1,230	2.74	1.00

Sources: Canadian Food Inspection Agency (n.d.), Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.), Saskatchewan Seed Growers' Association (n.d.), Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.)

Table 5.4: Provincial level summary statistics

Table 5.4 (a): Alberta

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	350	78,094.58	149,347.80
Share	%	350	1.64	3.31
Lag yield potential	bu/acre	255	59.24	16.38
Lag average yield	bu/acre	255	50.05	11.75
Lag variety specificity		212	4.02	2.69
Lag yield variance	$(bu/acre)^2$	212	103.73	116.94
Age	months	350	119.69	84.01
Age^2	$months^2$	350	21,362.78	28,861.41
Age^3	$months^3$	350	4,874,367.00	9,594,330.00
Protein	%	311	13.58	0.93
Stripe rust	scale 1-5	345	3.32	1.22
Loose smut	scale 1-5	350	2.90	1.16
Bunt	scale 1-5	347	3.49	1.38
Leaf spot	scale 1-5	346	2.33	0.68
Fusarium head blight	scale 1-5	345	2.16	0.97
Sprouting	scale 1-5	347	3.13	0.89
Lodging	scale 1-5	350	3.97	0.70
Height	scale 1-4	350	2.44	0.50
Head awn	dummy variable	239	0.59	0.49
Maturity rate	scale 1-5	350	2.97	0.70
Test weight	lb/bu	350	62.54	1.13
Seed weight	TKW	350	39.52	4.11

Table 5.4 (b): Manitoba

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	319	68,976.26	164,160.70
Share	%	319	3.01	7.23
Lag yield potential	bu/acre	239	60.84	14.03
Lag average yield	bu/acre	239	49.19	11.18
Lag variety specificity		208	2.68	2.41
Lag yield variance	bu/acre^2	208	87.72	64.16
Age	months	319	95.19	70.03
Age^2	months^2	319	13,950.24	18,924.29
Age^3	months^3	319	2,598,989.00	4,872,253.00
Protein	%	267	14.36	0.74
Stem rust	scale 1-5	319	4.50	0.66
Leaf rust	scale 1-5	319	4.11	1.08
Stripe rust	scale 1-5	276	3.32	1.01
Loose smut	scale 1-5	311	3.35	1.10
Bunt	scale 1-5	319	3.30	1.38
Leaf spot	scale 1-5	306	2.40	0.66
Fusarium head blight	scale 1-5	319	2.61	0.99
Sprouting	scale 1-5	225	3.58	1.04
Lodging	scale 1-5	319	4.20	0.72
Height	scale 1-4	319	2.66	0.72
Head awn	dummy variable	303	0.53	0.50
Maturity rate	scale 1-5	319	2.77	0.97
Seed weight	scale 1-4	205	1.66	0.90

Table 5.4 (c): Saskatchewan

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	561	76,728.63	152,101.30
Share	%	561	1.67	3.41
Lag yield potential	bu/acre	451	53.50	10.60
Lag average yield	bu/acre	451	44.86	9.06
Lag variety specificity		404	3.09	2.51
Lag yield variance	bu/acre^2	404	67.36	90.16
Age	months	561	97.11	72.12
Age^2	months^2	561	14,622.02	22,241.56
Age^3	months^3	561	2,921,949.00	7,166,271.00
Protein	%	561	14.15	0.85
Stem rust	scale 1-5	561	4.48	0.67
Leaf rust	scale 1-5	561	4.19	1.08
Stripe rust	scale 1-5	522	3.38	1.20
Loose smut	scale 1-5	555	2.87	1.17
Bunt	scale 1-5	561	3.63	1.34
Leaf spot	scale 1-5	554	2.45	0.67
Fusarium head blight	scale 1-5	561	2.23	1.01
Sprouting	scale 1-5	561	3.30	0.91
Lodging	scale 1-5	561	3.64	0.86
Height	scale 1-4	561	2.81	0.52
Head awn	dummy variable	561	0.69	0.46
Maturity rate	scale 1-5	561	2.58	1.13
Test weight	+/- kg/hl	561	-0.31	1.20
Seed weight	+/- mg	561	0.33	2.83

Sources: Canadian Food Inspection Agency (n.d.), Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.), Saskatchewan Seed Growers' Association (n.d.), Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.)

Table 5.5: Wheat class level summary statistics

Table 5.5 (a): HRS

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	827	80,242.60	157,526.70
Share	%	827	2.29	5.25
Lag yield potential	bu/acre	653	55.85	11.81
Lag average yield	bu/acre	653	46.35	9.41
Lag variety specificity		570	2.89	2.27
Lag yield variance	bu/acre^2	570	72.60	63.32
Age	months	827	103.57	73.74
Age^2	months^2	827	16,157.77	21,760.10
Age^3	months^3	827	3,206,290.00	6,284,941.00
Protein	%	783	14.38	0.49
Stripe rust	scale 1-5	757	3.16	1.03
Loose smut	scale 1-5	821	3.38	1.07
Bunt	scale 1-5	824	3.33	1.23
Leaf spot	scale 1-5	811	2.35	0.69
Fusarium head blight	scale 1-5	822	2.54	1.01
Sprouting	scale 1-5	752	3.48	0.97
Lodging	scale 1-5	827	3.91	0.73
Height	scale 1-4	827	2.75	0.57
Head awn	dummy variable	772	0.52	0.50
Maturity rate	scale 1-5	827	3.03	0.92

Table 5.5 (b): CPS

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	173	35,953.66	64,514.61
Share	%	173	0.77	1.52
Lag yield potential	bu/acre	120	70.59	15.20
Lag average yield	bu/acre	120	58.64	10.32
Lag variety specificity		99	5.02	3.40
Lag yield variance	bu/acre^2	99	159.73	175.87
Age	Months	173	101.41	68.14
Age^2	months^2	173	14,899.69	17,620.18
Age^3	months^3	173	2,662,993.00	4,255,357.00
Protein	%	160	12.46	1.15
Stripe rust	scale 1-5	170	3.05	1.33
Loose smut	scale 1-5	173	2.29	0.91
Bunt	scale 1-5	173	3.28	1.78
Leaf spot	scale 1-5	165	2.70	0.56
Fusarium head blight	scale 1-5	173	2.01	1.00
Sprouting	scale 1-5	161	2.63	0.88
Lodging	scale 1-5	173	4.39	0.82
Height	scale 1-4	173	2.18	0.52
Head awn	dummy variable	165	0.91	0.29
Maturity rate	scale 1-5	173	2.24	0.86

Table 5.5 (c): Durum

Variables	Unit	Obs.	Mean	St. Dev.
Acres	acres	184	103,259.20	201,864.10
Share	%	184	2.26	4.46
Lag yield potential	bu/acre	145	49.64	10.96
Lag average yield	bu/acre	145	41.97	8.69
Lag variety specificity		132	3.21	2.20
Lag yield variance	bu/acre^2	132	57.69	61.59
Age	Months	184	110.36	93.59
Age^2	months^2	184	20,891.21	35,805.81
Age^3	months^3	184	5,494,966.00	13,300,000.00
Protein	%	151	14.06	0.35
Stripe rust	scale 1-5	173	4.56	0.56
Loose smut	scale 1-5	184	1.92	0.70
Bunt	scale 1-5	184	4.76	0.50
Leaf spot	scale 1-5	184	2.45	0.64
Fusarium head blight	scale 1-5	184	1.55	0.50
Sprouting	scale 1-5	183	3.07	0.46
Lodging	scale 1-5	184	3.22	0.74
Height	scale 1-4	184	2.75	0.56
Head awn	dummy variable	123	1.00	0.00
Maturity rate	scale 1-5	184	1.92	0.91

Sources: Canadian Food Inspection Agency (n.d.), Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.), Saskatchewan Seed Growers' Association (n.d.), Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.)

5.5 Econometric model and estimation procedures

Building upon the theoretical model and the crop adoption literature, I estimate the effects of agronomic characteristics, including variety adaptability, and end-use values on wheat variety adoption at three levels:

(1) Prairie-wide,

(2) Provincial level: Alberta, Manitoba, and Saskatchewan, and

(3) Wheat class level: hard red spring (HRS), Canada prairie spring (CPS), and durum,

as it is plausible that adoption factors may vary in magnitude and significance by province and wheat class. These estimates use the econometric specification and estimation procedures presented below.

5.5.1 Econometric model

Equation (5.22) displays the simplest form of the variety adoption model, specified for the prairie-wide level:

$$\begin{aligned} adoption_{it} = \; & \alpha + \beta_1 yieldpotential_{i,t-1} + \beta_2 varietyspecificity_{i,t-1} \\ & + \beta_3 age_{it} + \beta_4 age_{it}^2 + \beta_5 age_{it}^3 + \beta_6 protein_{it} \\ & + \beta_7 striperust_{it} + \beta_8 loosesmut_{it} + \beta_9 bunt_{it} \\ & + \beta_{10} leafspot_{it} + \beta_{11} fusariumheadblight_{it} \\ & + \beta_{12} sprouting_{it} + \beta_{13} lodging_{it} + \beta_{14} height_{it} \\ & + \beta_{15} maturityrate_{it} + \eta_1 headawn_i + \varepsilon_{it} \end{aligned} \tag{5.22}$$

where α is the intercept, $i = 1, \dots, n$ varieties, and $t = 2009, \dots, 2018$.[28] Some variables are lagged one period to reflect that at the time of variety selection, farmers use information provided in the previous years yield publication. Provincial Seed Guides for the current growing season are available at the time of variety selection, so variables pulled from these sources do not need to be lagged. β and η represent the parameters to be estimated and ε_{it} is the error term. Finally, additional dummy variables for province and wheat class are included where appropriate.

5.5.2 Expected signs of independent variable parameters

Table 5.6 provides a summary of the explanatory variables, their type (time variant vs. time invariant; correlated with the variety specific effect or not), and the expected sign of the

[28] Provincial and wheat class level models differ slightly as some variables are not available across all three provinces and are therefore not included in the prairie-wide models (i.e., test weight, seed weight, etc.). Further, some variables become time invariant when measured within a province or wheat class (see Appendix B for more details).

estimated parameter with supporting reasoning.[29] It is important to note that this table includes slow changing variables in the set of time variant regressors and is based on the aggregate prairie model.

[29] For the Hausman-Taylor IV model, *lag yield potential*, *lag variety specificity*, *lag average yield*, *lag yield variance*, *protein*, and *test weight* are assumed to be the variables that are correlated with the variety specific effects. All other variables are argued to be exogenous. A table with justifications for these decisions is provided in Appendix A.

Table 5.6: Independent variable type and expected signs of the estimated parameters (using the prairie-wide dataset)

Independent variable	Time variant/ Time invariant/ Slow changing	Exogenous/ endogenous	Expected Sign	Reasoning
Lag yield potential	Time variant	Endogenous	(+)	Higher yield potential is expected to increase adoption.
Lag average yield	Time variant	Endogenous	(+)	Varieties with higher average yield are expected to have higher adoption rates.
Lag variety specificity	Time variant	Endogenous	(-)	Varieties with higher degrees of specificity are expected to be less widely adopted.
Lag yield variance	Time variant	Endogenous	(-)	Higher variability in yield is expected to be associated with lower adoption.
Life cycle (age, age^2, age^3)	Time variant	Exogenous		The number of months since a variety's release is expected to follow a diffusion path, initially positively associated with adoption but eventually subject to disadoption as newer varieties replace it.
Protein	Time variant	Endogenous	(+)	Higher percentage protein content increases the end-use value of wheat and should be associated with increased adoption of such varieties.
Stem rust*	Slow changing	Exogenous	(+)	It is expected that increases in stem rust tolerance ratings increase variety adoption.
Leaf rust*	Slow changing	Exogenous	(+)	It is expected that increases in leaf rust tolerance ratings increase variety adoption.
Stripe rust	Slow changing	Exogenous	(+)	It is expected that increases in stripe rust tolerance ratings increase variety adoption.
Loose smut	Slow changing	Exogenous	(+)	It is expected that increases in loose smut tolerance ratings increase variety adoption.
Bunt	Slow changing	Exogenous	(+)	It is expected that increases in bunt tolerance ratings increase variety adoption.

Leaf spot	Slow changing	Exogenous	(+)	It is expected that increases in leaf spot tolerance ratings increase variety adoption.
Fusarium head blight	Slow changing	Exogenous	(+)	It is expected that increases in Fusarium head blight tolerance ratings increase variety adoption.
Sprouting	Slow changing	Exogenous	(+)	It is expected that increases in sprouting resistance ratings increase variety adoption.
Lodging	Slow changing	Exogenous	(+)	It is expected that increases in lodging tolerance ratings increase variety adoption.
Height	Slow changing	Exogenous	(-)	It is expected that increases in height ratings (i.e., taller varieties) decrease variety adoption.
Head awn	Time invariant	Exogenous	(+)	Head awn is expected to positively impact adoption.
Maturity rate	Slow changing	Exogenous	(+)	A positive association between faster maturity rates and adoption is expected.
Test weight*	Slow changing	Endogenous	(+)	Increased test weight is expected to increase adoption as it leads to a higher grain grade.
Seed weight*	Slow changing	Exogenous	(-)	Increased seed weight increases the seeding rate. Therefore, it is expected that heavier seeds increase seeding costs and negatively impact adoption.

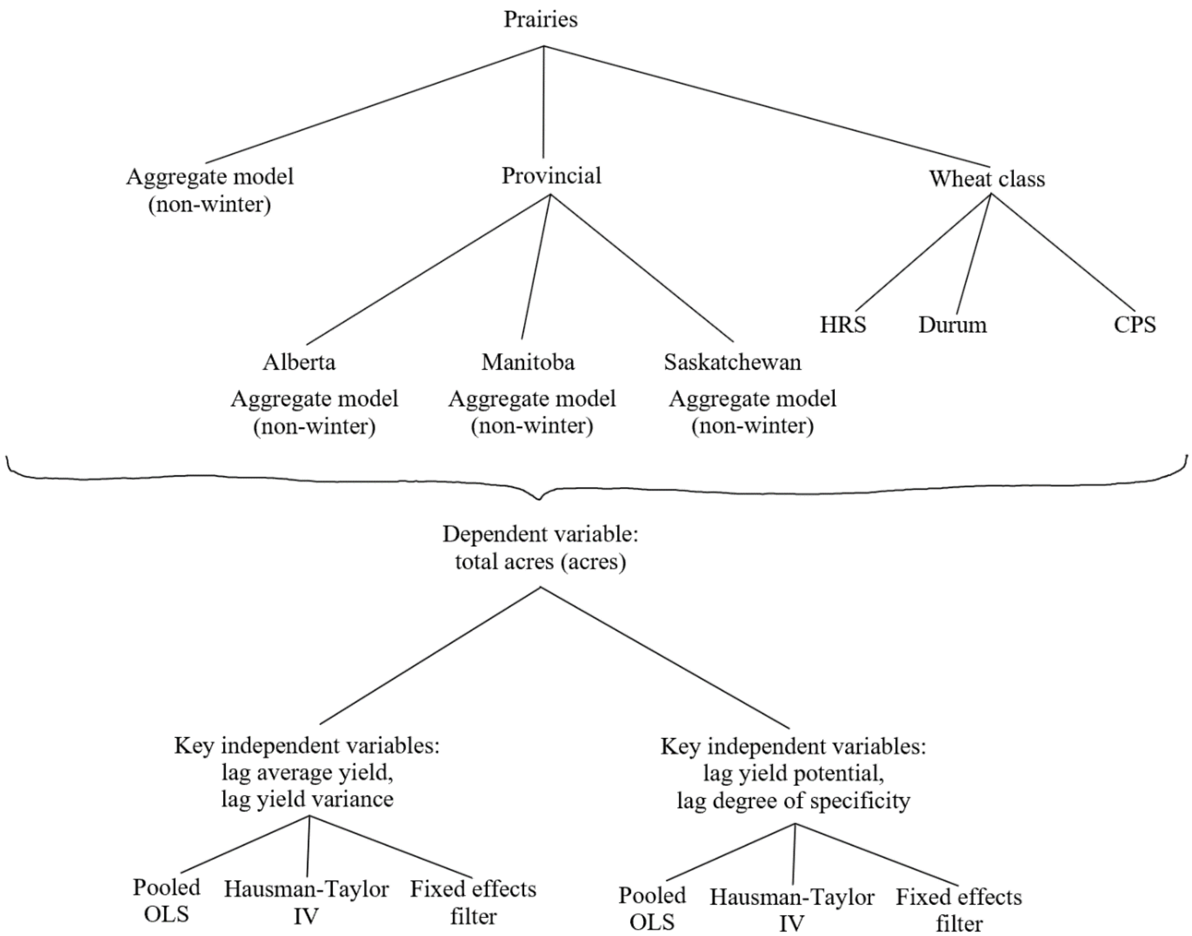
* These variables are not included in prairie-wide and wheat class level modeling due to data limitations.

5.5.3 Estimation procedures

Three sets of regressions are estimated, one for each adoption level (see Table 5.7). Each set contains pooled OLS, Hausman-Taylor IV, and FEF models, as shown in Figure 5.1 below. Specifications for these models vary slightly from Equation (5.22), depending on the level of adoption examined and the regression model. As previously mentioned, I measure the dependent variable $adoption_{it}$ as total insured acres ($acres_{it}$) allocated to variety i in period t. Additionally, I estimate the adoption model using $share_{it}$ as the dependent variable with two-limit Tobit and fixed effects Tobit approaches in order to examine the robustness of the results. However, these are considered secondary sets due to potential bias limitations and therefore not included in the primary sets of regressions.[30]

[30] See Appendix D for these results.

Figure 5.1: Map of regressions



Control independent variables:

age, age^2, age^3, height, lodging, sprouting, disease tolerance (stem rust, leaf rust, stripe rust, loose smut, bunt, leaf spot, fusarium head blight), head awn, maturity rate, protein, test weight, seed weight, wheat class and province dummy variables

Table 5.7: Overview of the sets of regression models

Set	Subset	Models	Key independent variables	Excluded control variables
(1): Prairies		1, 3, 5	Lag average yield, lag yield variance	Excludes leaf rust, stem rust, test weight and seed weight
		2, 4, 6	Lag yield potential, lag variety specificity	
(2): Provincial	Alberta	7, 9, 11	Lag average yield, lag yield variance	Excludes stem rust and leaf rust
		8, 10, 12	Lag yield potential, lag variety specificity	
	Manitoba	13, 15, 17	Lag average yield, lag yield variance	Excludes test weight
		14, 16, 18	Lag yield potential, lag variety specificity	
	Saskatchewan	19, 21, 23	Lag average yield, lag yield variance	
		20, 22, 24	Lag yield potential, lag variety specificity	
(3): Wheat class	Hard red spring	25, 27, 29	Lag average yield, lag yield variance	Excludes leaf rust, stem rust, test weight and seed weight
		26, 28, 30	Lag yield potential, lag variety specificity	
	Canada prairie spring	31, 33, 35	Lag average yield, lag yield variance	Excludes leaf rust, stem rust, test weight and seed weight
		32, 34, 36	Lag yield potential, lag variety specificity	
	Durum	37, 39, 41	Lag average yield, lag yield variance	Excludes leaf rust, stem rust, test weight and seed weight
		38, 40, 42	Lag yield potential, lag variety specificity	

Set (1) estimates adoption factors for all non-winter wheat varieties at the prairie-wide level, using data spanning from 2009 to 2018. Models (1), (3), and (5) contain the key parameter of interest, the lag variety specificity. The remaining models in this set are included for comparative purposes and alternatively use lag yield variance to measure yield volatility. I exclude stem rust and leaf rust tolerances due to lack of available data in Alberta. Additionally, I exclude seed weight and test weight due to differences in measurement across provinces.

Provincial aggregate estimates for all non-winter varieties form Set (2). The available data spans from 2013 to 2018 for Alberta, and 2009 to 2018 for Manitoba and Saskatchewan.

Odd numbered models between Model (7) and Model (24) contain lag yield potential and lag variety specificity, while even numbered models in this set use lag average yield and lag yield variance for each province. Leaf rust and stem rust are not included in Alberta due to lack of data availability. Similarly, test weight is not available for Manitoba.

Set (3) estimates varietal attribute effects at the wheat class level for those with sufficient data (i.e., HRS, CPS, Durum). As in Set (2), odd numbered models in this set use lag variety specificity as an independent variable, while even numbered models rely on lag yield variance Since these wheat class level models use the combined prairie-wide dataset, I again exclude stem rust, leaf rust, test weight and seed weight from the set of regressors.

The decision to examine varietal adoption decisions for three different levels stems from the plausible differences in varietal trait preferences across provinces and wheat classes. While prairie-wide modeling uses the largest dataset for an aggregate analysis of variety adoption choices, the analysis at this level provides limited information on inherent differences across provinces and wheat classes. Dummy variables for provinces included in modeling for the prairie-wide level indicate how much total acreage of a particular variety changes by province, relative to the omitted provincial dummy, Saskatchewan, which accounts for the largest share of observations. But these values do not reveal anything about the differences in effects of variety traits on adoption unless I include interaction terms. Given the large number of regressors, this approach is unwieldy. Instead, I use provincial models for Alberta, Manitoba, and Saskatchewan to gain insights into differences in variety trait preferences between provinces. I take a similar approach for wheat classes, where it is plausible that the effects of some variety traits will differ. For example, hard red spring varieties generally have higher protein content, which may reduce the relative importance of this factor in selecting a variety when the scope is limited to this class. Since the number of interaction terms required again substantially diminishes the available degrees of freedom in the models, I conduct analyses at the wheat class level for three major wheat classes with sufficient data: HRS, CPS, and durum. Ultimately, these provincial and wheat class level analyses are limited by reduced observations, however, they do provide valuable insights into trait preference differences across each level with minimal loss of degrees of freedom.

In total, this empirical approach estimates a combined 42 models across various levels. From the discussions in section 5.3 and poolability F-testing indicating that sufficient variety specific heterogeneity exists to support a panel data approach, the FEF is the favoured empirical model. This is in part due to the lower number of required assumptions, relative to the Hausman-Taylor model. However, by presenting the least squares estimations from the FEF along side the pooled OLS and Hausman-Taylor IV models, the empirical approach provides a means to examine the robustness of the FEF results. Additionally, *Appendix D* provides the maximum likelihood estimates of the Tobit and fixed effects Tobit models, offering further comparison to the results available of the FEF, presented in the next chapter.

Chapter 6: Results and discussion

6.1 Introduction

In this chapter, I present empirical results for factors of variety adoption across the Canadian Prairies. I include the results of three estimated models (pooled OLS, Hausman-Taylor IV, and FEF) at each level (prairie, provincial, and wheat class) using acres allocated to variety *i* in period *t* as the dependent variable. In each case, empirical modeling is based on varieties grown in a minimum of four risk areas in a given year and province. Prior to presenting these results, I provide a brief discussion of the empirical considerations contributing to the selection of results presented in this chapter. In the following sections, even numbered models use *lag yield potential* and *lag variety specificity* as the key independent variables, while odd numbered models use *lag average yield* and *lag yield variance*. The discussion centres on the FEF results, as this model is the best fit for this analysis.

6.2 Empirical considerations

The decision to estimate three empirical models for varieties grown in a minimum of four risk areas within a province and year at three different levels of adoption stems from several considerations. These include minimum requirements on the amount of risk area level data for reliable yield variables and potential model biases. The following discussion elaborates on some of these considerations.

Due to the nature of measurement for both *lag yield variance* and *lag variety specificity*, the main discussion focuses on empirical results based on varieties grown in at least four risk areas, with full dataset results available in Appendix D. Both yield variance and variety specificity are functions of the number of risk areas with available data and when only one risk area is available, neither measure is calculable. In order for either measure to be a reliable measure of adaptability, the data must be available in at least a few different risk areas. For example, if only one yield data point is available for a variety at the risk area level, variety specificity μ_i is:

$$\mu_i = \frac{y_i^{max} - y_i^{min}}{RA} = 0 \tag{6.1}$$

where $Y_{max} = Y_{min}$ since only one yield data point is included in the calculation. In this case, $\mu_i = 0$ suggests that the variety is perfectly adaptable to all growing conditions but this is misleading as it was grown in only one specific location. A similar issue is observed for yield variance, where values calculated using only one observation are meaningless. Even when two are available, the variance is not very helpful in identifying the adaptability of the variety. However, excluding data from varieties grown in fewer risk areas in a given year and province does truncate the available data. Balancing this with accuracy in these two measures, I choose a somewhat arbitrary minimum of four risk areas of data within a year and province at a cost of reduced total insured acreage represented by the model, ranging from 1.33% to 6.36% depending on the modeling level (see Table 6.1).

Table 6.1: Share of total acreage lost due to minimum four risk area requirement

Analysis level	Share of total acreage lost by truncation (below min 4 risk areas)
Prairies	3.23%
Alberta	6.25%
Manitoba	1.33%
Saskatchewan	2.28%
Hard red spring	2.12%
Canadian Prairie spring	4.89%
Durum	6.36%

Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), & Manitoba Agricultural Services Corporation (n.d.)

Pooled OLS models for each level of analysis, while included, likely suffer from omitted variable bias as poolability F-tests indicate that sufficient variety heterogeneity is present to justify a panel data econometric approach.[31] The Hausman-Taylor IV model's usefulness is also limited. As mentioned in the previous chapter, for the Hausman-Taylor IV model I assume only the yield related variable, protein, and test weight are endogenous with respect to variety specific

[31] See Appendix E for poolability F-test results.

effects. I assume all other traits are exogenous (see justifications in Appendix A). However, it is plausible that extent of varietal resilience to diseases is not independent of other unobservable variety genetics. As it is this observed extent of resistance measuring varietal disease tolerance here, it is likely that the Hausman-Taylor IV model estimates are biased under these exogeneity assumptions. Alternatively, assuming all disease resistance ratings are endogenous presents a problem for model identification due to insufficient internal IVs. This limitation of the Hausman-Taylor model is why the analysis of this chapter focuses on the FEF estimates, where fewer assumptions are necessary. In fact, at the prairie-wide level the FEF model requires only the additional assumption that head awn is exogenous from the variety specific effects.[32] As the head of a variety is either awned (bearded) or not, this assumption is reasonably sound.

6.3 Prairie-wide results

Estimation results at the prairie-wide level in Table 6.2 reflect data from varieties grown in a minimum of four risk areas. As noted in the previous chapter, Models (1), (3), and (5) include *lag average yield* and *lag yield variance* as the key independent variables, in line with existing literature (Dahl et al., 1999). Models (2), (4), and (6) pair *lag yield potential* and *lag variety specificity* as the key regressors, as per the conceptual framework in chapter three and the approach of Torshizi (2015). Simple pooled OLS regressions form Models (1) and (2),[33] while Models (3) and (4) use the Hausman-Taylor IV approach. The remaining two models, Models (5) and (6), use the preferred FEF estimation procedure. Testing reveals heteroskedasticity of the errors, due to differences in variety effects on adoption.[34] To address this, all models use corrected standard errors, that are clustered by variety.

Results for the pooled OLS models indicate a higher explanatory power when *lag yield potential* and *lag variety specificity* are the key independent variables. Model (1), explaining approximately 19% of the variation around the mean adoption level indicates that taller varieties of wheat are associated with lower adoption levels. Faster maturity rates negatively affect

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[32] This assumption is in addition to the standard FE assumptions, which include the OLS assumptions.
[33] Saskatchewan and the hard red spring wheat class represent the province and wheat class with the largest acreage. These are omitted from the pooled OLS model to avoid the dummy variable trap.
[34] See Appendix E for heteroskedasticity testing results.

adoption levels, while most disease tolerances and protein content appear to have no significant effects with the exception of lodging resistance. Additionally, *lag average yield* displays no significant association with adoption levels. However, significance of the variety life cycle indicators (i.e., $age, age^2,$ and age^3) support an S-shaped adoption pattern for wheat variety life cycles, with rapid growth in adoption, followed by a period of continued growth but at a declining rate as the variety approaches the end of its life cycle. Model (2) presents similar findings for the estimated effect of variety height. However, by using *lag yield potential* and *lag variety specificity* as key independent variables, the explanatory power of this model increases to 29%. In each case, these variety traits are statistically significant at the 5% level. Model (2) also points to significant effects of *lag yield potential* and *lag variety specificity* on adoption at the 1% level, each with the expected signs (i.e., positive and negative, respectively). This negative relationship between variety specificity and adoption levels suggests that more adaptable varieties are in fact more widely adopted. These should be interpreted cautiously though, as estimates from the pooled OLS approach do not account for variety specific heterogeneity – heterogeneity which poolability F-tests indicate is present – which means that these pooled OLS estimates are likely biased.

Using the Hausman-Taylor IV in an effort to account for these variety effects, I find that the estimates in Models (3) and (4) differ from the previous two models. While taller varieties remain negatively correlated with variety adoption in Model (3), this result does not hold in Model (4). Further, lodging resistance effects are now significant at the 10% level and positive in both models. Interestingly, it appears from these estimates that tolerance to loose smut negatively impacts adoption, albeit only when at a significance level of 10% in Model (4). The life cycle of varieties continues to be significant at a 5% significance level, supporting a S-shaped adoption path. Finally, for the key independent variables in either model, only *lag variety specificity* is significant at the 10% level, again indicating a positive association between variety adaptability and variety adoption. However, as I discuss in chapter five, these estimates depend on a large number of assumptions that may or may not be correct.

With this in mind, results for the favoured FEF model that account for variety specific effects and rely on fewer strong assumptions are the primary focus of this analysis. As in the pooled OLS model, explanatory power is relatively higher for Model (6), the model which relies on *lag yield potential* and *lag variety specificity*, when compared to Model (5). Further, Models (5) and (6) have Step 1 R^2 values of 52% and 56%, respectively, which are higher than those from the comparable pooled OLS models. The intercept, indicating a baseline of Saskatchewan hard red spring varieties acreage when all independent variables take the value zero, is positive and significant at the 5% significance level in both Models (5) and (6). Variety height again negatively impacts adoption, though for a 10% significance level in these models. Protein content is also negatively associated with adoption, an interesting observation that supports the idea that some trade-offs exist between varietal traits.[35] Most disease tolerances do not appear to significantly impact variety decisions, with one exception, fusarium head blight tolerance. Increased tolerance to this particular disease appears to decrease variety popularity, possibly due to an unknown trade-off between this tolerance and another varietal trait, as I discuss later in this chapter. Estimates for both Model (5) and (6) indicate that life cycles of varieties take an S-shaped adoption path. Estimates of the FEF for *lag average yield* and *lag yield variance* in Model (5) are again not significantly different from zero. *Lag yield potential* and *lag variety specificity* are significant at the 1% level, taking the expected positive and negative signs respectively. Magnitudes of the estimated associations between variety adoption and these two variables are lower in the FEF, relative to the pooled OLS. Since it is the FEF that accounts for variety specific heterogeneity with higher explanatory power, I place more confidence in these estimates. Finally, the second stage looks at the single time invariant variety trait for this level of analysis, variety head awn, finding a negative and significant effect on variety acreage in Model (5) only.

Overall, the results of the FEF analysis at the prairie-wide level indicates that variety height, fusarium head blight tolerance, protein content, yield potential, and varietal adaptability are significantly correlated with variety adoption decisions. Additionally, variety adoption life cycles appear to take an S-shape. These results are generally consistent with the other modelling approaches presented in Table 6.2 and in Appendix D, though magnitudes and significance of

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[35] Iqbal et al. (2007) indicate that there is a negative relationship between protein content and yield which generates a trade-off between these two traits. Evidence of this relationship is observed in Table 5.5, where differences in yield potential and protein averages for CPS and HRS classed varieties are shown (i.e., within the dataset, CPS varieties are higher yielding on average, while HRS varieties have higher average protein contents).

trait effects vary due to various differences in the statistical properties of each model. Further, these results are generally consistent with the findings of Barkley and Porter (1996) and Dahl et al. (1999), though with fewer disease tolerances presenting significant estimated effects here. An additional observation worth noting is that, in all models, explanatory power is higher when the yield potential and variety specificity are included, relative to when the key variables are average yield and yield variance. This suggests that when paired with variety yield potential, adaptability, measured by the degree of variety specificity, better explains variations in varietal acreage on the Canadian Prairies.

Table 6.2: Prairie-wide estimates

Variables	(1) Pooled OLS	(2) Pooled OLS	(3) HT-IV	(4) HT-IV	(5) FEF Step 1	(5) FEF Step 2	(6) FEF Step 1	(6) FEF Step 2
Dependent variable: acres								
Lag yield potential		3,770***		418.77			3,289***	
		(1,083)		(719.05)			(858.14)	
Lag average yield	1,204		-896.46		563.64			
	(1,427)		(718.58)		(812.90)			
Lag variety specificity		-41,649***		-11,559*			-30,068***	
		(8,066)		(5,942)			(8,913)	
Lag yield variance	-234.92*		87.82		46.19			
	(124.91)		(62.79)		(132.11)			
Age	3,224**	1,669	4,782**	4,192**	4,476**		2,762	
	(1,359)	(1,156)	(2,227)	(2,106)	(2,106)		(2,010)	
Age^2	-17.70**	-8.94	-40.01***	-35.45***	-36.71***		-25.63**	
	(7.67)	(6.45)	(14.50)	(13.70)	(13.60)		(12.67)	
Age^3	0.03**	0.01	0.07***	0.06**	0.06**		0.04**	
	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)		(0.02)	
Protein	25,049	12,488	7,761	6,159	-151,853**		-125,068**	
	(28,967)	(26,598)	(102,519)	(95,918)	(75,411.23)		(60,256)	
Stripe rust	6,422	9,896	2,392	6,306	-60,807		-48,626	
	(10,429)	(9,485)	(14,454)	(14,354)	(41,358)		(35,396)	
Loose smut	-3,629	1,602	-44,143**	-39,389*	-17,475		-13,631	
	(13,857)	(13,528)	(22,253)	(22,501)	(42,204)		(40,028)	
Bunt	-22,462	-19,988	20,274	17,192	46,245		37,441	
	(18,675)	(16,475)	(32,615)	(32,174)	(46,520)		(43,444)	
Leaf spot	36,905	29,476	-5,787	-6,284	2227		-17,272	
	(28,053)	(26,213)	(32,543)	(36,147)	(79,468)		(69,042)	
Fusarium head blight	2,571	-4,949	-23,622	-27,221	-111,289*		-121,078**	
	(18,617)	(17,096)	(23,994)	(23,271)	(56,312)		(56,814)	
Sprouting	-3,582	-5,965	-3,251	-6,977	-32,821		-21,212	
	(14,797)	(13,878)	(23,840)	(23,184)	(73,001)		(64,992)	
Lodging	25,138*	11,574	65,963*	63,505*	44,074		36,013	
	(14,596)	(14,632)	(34,942)	(34,508)	(33,446)		(28,752)	
Height	-75,535**	-60,921**	-47,565*	-42,697	-77,844*		-57,079*	
	(31,715)	(29,013)	(27,907)	(26,549)	(40,759)		(31,484)	

Head awn	24,120	31,290	-39,295	-23,472		-149,917**		-91,188
	(42,535)	(39,176)	(90,216)	(89,236)		(68,196)		(57,513)
Maturity rate	-18,579*	-11,345	9698	13,982	-16,795		-5,743	
	(9,887)	(9,514)	(10,556)	(11,084)	(18,742)		(19,069)	
Provincial dummy variables	✓	✓	✓	✓	✓		✓	
Wheat class dummy variables	✓	✓						
Constant	-279,835	-102,979	-60,825	-70,016	2,734,145**	97,064**	2,278,531**	58,369
	(532,313)	(485,326)	(1,580,083)	(1,475,232)	(1,265,911)	(46,598)	(1,014,711)	(38,860)
Observations	529	529	529	529	538	529	538	529
R^2	0.19	0.29			0.52	0.07	0.56	0.03
Number of varieties	76	76	76	76	76	76	76	76

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.4 Provincial results

As noted in chapter five, it is plausible that varietal trait preferences vary across provinces. By dividing the dataset into provinces and completing provincial level analyses, I gain insights into some of these differences. The following discussion looks at these results, starting with an analysis of Alberta's wheat varietal trait preferences, followed by similar analyses for Manitoba and Saskatchewan. This section concludes with a brief summary of the empirical findings at the provincial level of analysis.

6.4.1 Alberta

Alberta's estimates rely on the subset of data sourced from its provincial publications between 2013 and 2018. As in the previous table, the first two models (i.e., Models (7) and (8)) present estimates from pooled OLS regressions. Following these are results for the Hausman-Taylor IV (i.e., Models (9) and (10)) and the preferred FEF (i.e., Models (11) and (12)) approaches. Again, even numbered models use *lag yield potential* and *lag variety specificity* as the key regressors, while odd numbered models use *lag average yield* and *lag yield variance*. Post-estimation testing again indicates the presence of heteroskedasticity due to varietal differences; therefore, I include corrected standard errors, clustering on variety. [36]

In the pooled OLS regressions, explanatory power is higher when *lag yield potential* and *lag variety specificity* are the key independent variables. Model (7) explains approximately 51% of the variation around the mean adoption level in Alberta, compared to 57% in Model (8). Provincial modeling includes test and seed weights, but neither show a statistically significant relationship with adoption decisions in Alberta. Models (7) and (8) indicate a link between variety acreage and faster maturity rates at a 5% significance level. Similarly, varieties more tolerant to stripe rust and loose smut diseases are grown on more acres. Model (8) confirms the cubic life cycle for variety adoption, though Model (7) suggests that a quadratic life cycle control may be sufficient in that model. Finally, *lag yield potential* and *lag variety specificity* show the expected significant associations with variety acreage, with at least 90% confidence in these

[36] See Appendix E for heteroskedasticity testing results.

estimates. However, while these pooled OLS results provide some insights, the differentiated nature of varieties is ignored in these estimates.

The panel data approach of the Hausman-Taylor IV generates qualitatively similar estimates, though the magnitudes differ. The main differences between these estimates and those of the pooled OLS models are the statistical significance of leaf spot tolerance and the lack of significance of any of the key variables. Models (9) and (10) point to improved leaf spot tolerance negatively impacting variety adoption, while *lag yield potential* and *lag variety specificity* no longer display any statistical significance.

Turning to the FEF results in Models (11) and (12), the insignificance of the key independent variables remains. From Step 1 of each model, varietal height effects lack significance, but lodging resistance in Model (11) positively impacts variety acreage at the 1% significance level. Increased bunt tolerance is negatively associated with varietal adoption in both models, while increased stripe tolerance positively relates to adoption, though at the 5% level. This negative correlation between variety bunt tolerance and adoption may stem from an unaddressed trade-off with another varietal trait or may potentially be from limited within variety variations challenging the accuracy of empirical estimates for this trait. Age to the second-degree polynomial shows significance, suggesting a quadratic life cycle pattern for varieties in Alberta. Finally, the explanatory power of Step 1 in both Models (11) and (12) is relatively high at 92%.

Step 2 of the FEF contains more estimates than prairie level modeling did, as variety head awn, height, maturity, fusarium head blight tolerance, and loose smut tolerance are time invariant for Alberta. Of these, both loose smut resistance (at the 5% significance level) and variety head awn (at the 1% significance level) appear to be assets for varieties, with both associated with increased acreage. Each of these models explain over 25% of the variations around the mean variety specific fixed effect.

From these findings, it appears that tolerances to stripe rust, loose smut, bunt, and variety head awn are the significant factors in explaining Albertan variety adoption decisions.[37] However, the lack of significance of either yield variable suggests that caution is necessary when using these estimates. These results may be due to a small number of observations containing full

[37] For additional modelling approach results, see Appendix D.

information and a large number of regressors and panels (i.e., varieties), limiting the degrees of freedom of each model. Alternatively, insufficient within variety variability in some variables may contribute to the limitations of these results.

Table 6.2: Alberta provincial estimates

Variables	(7)	(8)	(9)	(10)	(11)		(12)	
	Pooled OLS	Pooled OLS	HT-IV	HT-IV	FEF		FEF	
					Step 1	Step 2	Step 1	Step 2
	Dependent variable: acres							
Lag yield potential		2,980*		424.90			-191.23	
		(1,574)		(1,159)			(1,145)	
Lag average yield	668.94		793.13		159.93			
	(2,011)		(1,020)		(1,107)			
Lag variety specificity		-33,024***		-213.67			833.44	
		(10,376)		(3,454)			(3,562)	
Lag yield variance	-133.92		173.86*		150.82*			
	(167.04)		(91.78)		(86.27)			
Age	10,172**	9,487**	11,320**	10,404**	8,837**		8,556**	
	(4,821)	(4,606)	(4,669)	(4,605)	(4,102)		(4,135)	
Age^2	-69.58*	-66.13*	-85.27**	-74.92**	-63.00*		-58.83*	
	(37.58)	(35.56)	(38.63)	(37.09)	(32.75)		(32.19)	
Age^3	0.15	0.15*	0.17*	0.14	0.10		0.09	
	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)		(0.07)	
Protein	-53,794	-86,528	84,669	85,837	25,839		40,901	
	(96,591)	(82,186)	(83,357)	(80,163)	(46,773)		(49,640)	
Stripe rust	55,700*	55,119**	31,739**	33,734**	23,759**		27,217***	
	(27,967)	(23,879)	(13,816)	(13,784)	(9,620)		(9,763)	
Loose smut	85,965**	77,519**	70,613**	70,412**		125,992**		123,420**
	(40,837)	(35,626)	(30,550)	(30,870)		(58,068)		(56,418)
Bunt	1,972	46.15	-11,445	-18,294	-229,202***		-236,549***	
	(30,517)	(27,681)	(25,021)	(25,813)	(33,800)		(34,891)	
Leaf spot	-102,531	-101,215	-173,020***	-166,688***	-		-	
	(93,157)	(86,250)	(51,608)	(53,570)				
Fusarium head blight	-11,474	9,298	-54,735	-51,912		-116,845		-112,335
	(36,480)	(30,985)	(42,449)	(40,715)		(107,181)		(104,148)
Sprouting****	-1,528	-804.28	-662.28	-100.70		31,579		29,803
	(29,002)	(23,532)	(38,869)	(37,284)		(81,083)		(77,290)
Lodging	-38,250	-85,997	59,686	53,813	34,677*		21,880	
	(107,618)	(94,657)	(43,129)	(43,931)	(19,113)		(19,499)	
Height	-155,303	-143,767	-66,008	-57,051		40,209		39,761
	(118,428)	(106,342)	(111,342)	(110,548)		(158,639)		(155,417)
Head awn	-6,167	-27,906	-153.85	13,166		499,846***		514,799***
	(115,162)	(107,182)	(95,953.21)	(93,539)		(152,242)		(151,606)

Maturity rate	165,098**	145,998**	114,931**	105,779**	97,214		96,609	
	(80,527)	(70,353)	(46,269)	(45,679)	(95,870)		(85,352)	
Test weight	6,061	5,406	8,567	15,923	-5,879		-298.21	
	(34,327)	(27,460)	(26,577)	(26,660)	(14,404)		(14,076)	
Seed weight	822.69	3,361	-8,263	-6,056	1,286		5,380	
	(21,607)	(17,813)	(23,642)	(22,308)	(24,495)		(22,371)	
Wheat class dummy variables	✓	✓						
Constant	-61,561	520,692	-1,855,890	-2,358,942	105,026	-681,966	-512,860	-681,795
	(2,506,127)	(2,104,857)	(2,439,046)	(2,420,318)	(1,074,955)	(510,316)	(1,072,007)	(487,387)
Observations	103	103	103	103	114	103	114	103
R^2	0.51	0.57			0.92	0.27	0.92	0.28
Number of varieties	32	32	32	32	37	32	37	32

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**** sprouting is time invariant in Alberta when the restriction of a minimum of four risk areas is imposed

6.4.2 Manitoba

Estimated results for Manitoba, presented in Table 6.4, include two pooled OLS models (Models (13) and (14)), two Hausman-Taylor IV (Models (15) and (16)), and two FEF (Models (17) and (18)). As in the previous results tables, even numbered regressions rely on *lag yield potential* and *lag variety specificity* as the key regressors. Again, due to the presence of heteroskedasticity, I cluster standard errors on varieties. [38]

Results of the pooled OLS approach indicate using *lag yield potential* and *lag variety specificity* as the key independent variables increases the explanatory power by approximately 1%. However, none of the key independent variables is statistically significant. Based on Models (13) and (14), it appears that only faster maturity rates improve adoption rates. Other traits reporting significant negative effects (for a 10% significance level) include stem rust, loose smut, and sprouting resistances. Variety head awn and seed weights also decrease adoption rates according to the pooled OLS estimates.

Accounting for variety specific heterogeneity, estimates of the Hausman-Taylor IV approach differ slightly. Results indicate negative associations between varietal acreage and variety specificity, stem rust resistance, and fusarium head blight resistance for a 10% significance level. Estimated results again support an S-shaped variety life cycle. In contrast to findings of the prairie-wide analysis, Models (15) and (16) report positive coefficients for variety protein content. Further, improved sprouting resistance appears a significant asset to varieties.

Estimates from the preferred FEF models show reduced explanatory power for Step 1 when *lag average yield* and *lag yield variance* are the key independent variables, consistent with observations from the pooled OLS regressions. In Models (17) and (18), estimates of all four key variable effects are insignificant. Higher stem rust and fusarium head blight tolerances exhibit negative associations with variety acreage, while all of the time invariant traits from Step 2 of the FEF show no consequential effects on varietal adoption.

Placing more weight on the estimates of Models (17) and (18) due to the more desirable properties of the FEF empirical approach, I find two disease tolerances (i.e., stem rust and fusarium head blight) contribute to Manitoba producer variety decisions. However, all yield

[38] See Appendix D for heteroskedasticity testing results.

related variety traits lack consequential effects for this level of modeling. Given the relatively small number of observations, paired with high numbers of regressors which limit degrees of freedom, confidence in these results for Manitoba is somewhat limited.

Table 6.3: Manitoba provincial estimates

Variables	(13)	(14)	(15)	(16)	(17)		(18)	
	Pooled OLS	Pooled OLS	HT-IV	HT-IV	FEF		FEF	
					Step 1	Step 2	Step 1	Step 2
Dependent variable: acres								
Lag yield potential		-2,184		-1,500			162.24	
		(2,287)		(1,226)			(1,348)	
Lag average yield	-2,245		-660.08		951.15			
	(2,056)		(930.30)		(2,294)			
Lag variety specificity		-20,326		-9,306*			-16,651	
		(12,229)		(5,294)			(13,939)	
Lag yield variance	-276.21		-239.40		0.89			
	(237.00)		(150.71)		(279.15)			
Age	-2,224	-2,265	875.31	881.37	6,185		5,393	
	(2,827)	(2,636)	(895.92)	(748.04)	(4,160)		(3,876)	
Age^2	3.70	1.30	-35.54***	-35.14***	-77.37**		-71.61**	
	(24.40)	(23.46)	(4.26)	(4.08)	(32.14)		(27.59)	
Age^3	0.00	0.01	0.09***	0.09***	0.17**		0.16**	
	(0.05)	(0.05)	(0.01)	(0.01)	(0.07)		(0.06)	
Protein	87,290	99,599	104,148*	117,704*	368,235		332,771	
	(79,153)	(75,478)	(58,550)	(60,351)	(355,545)		(311,616)	
Stem rust	-206,713*	-191,110*	-233,446***	-228,570***	-246,191***		-249,842***	
	(106,768)	(94,665)	(65,284)	(63,058)	(82,940)		(70,409)	
Leaf rust	18,227	23,302	-17,915	4,642		-138,506		-110,995
	(89,599)	(90,261)	(154,052)	(154,953)		(170,901)		(151,555)
Stripe rust	8,895	-1,655	10,529	6,047	63,221		58,414	
	(39,175)	(32,452)	(13,051)	(12,422)	(56,656)		(52,125)	
Loose smut	-151,369**	-138,707**	47,733	37,322		52,231		45,625
	(59,014)	(57,030)	(68,091)	(68,311)		(32,939)		(29,262)
Bunt	49,415	37,509	-32,569	-30,396	-64,362		-58,198	
	(36,396)	(34,309)	(27,463)	(25,858)	(45,514)		(37,364)	
Leaf spot	-456,512***	-419,278***	-236,619	-227,924		49,198		31,069
	(94,960)	(104,285)	(334,297)	(316,967)		(261,367)		(231,385)
Fusarium head blight	54,752	43,541	-142,654***	-130,862***	-186,256***		-173,566***	
	(143,946)	(132,230)	(23,948)	(26,171)	(62,012)		(58,241)	
Sprouting	-65,140***	-58,918**	108,187***	121,543***	67,273		68,782	
	(19,612)	(23,541)	(22,933)	(29,539)	(79,781)		(86,546)	
Lodging	12,054	17,259	-32,628	-2,307		3,222		18,667

	(21,834)	(28,336)	(188,863)	(187,936)		(127,129)		(115,019)
Height	-48,544	-43,798	-23,744	-30,288	-21,148		-18,092	
	(32,077)	(28,056)	(33,564)	(29,764)	(57,532)		(53,067)	
Head awn	-807,357***	-744,937***	-32,264	-17,775		83,459		73,128
	(207,540)	(223,053)	(259,141)	(248,847)		(213,508)		(188,126)
Maturity rate	-618,632***	-561,104***	-334,249	-308,709		-129,594		-124,222
	(103,384)	(113,465)	(298,004)	(282,514)		(311,728)		(275,929)
Seed weight	-281,724**	-248,668*	-45,485	-13,888		-12,850		5,561
	(127,755)	(136,975)	(326,043)	(312,943)		(239,629)		(212,026)
Wheat class dummy variables	✓	✓						
Constant	4,266,404**	3,719,046*	1,582,214	1,031,482	-3,741,291	567,515	-3,181,587	412,263
	(1,718,851)	(1,898,572)	(3,706,283)	(3,557,722)	(4,987,587)	(2,596,315)	(4,327,323)	(2,300,910)
Observations	67	67	67	67	118	67	118	67
R^2	0.77	0.78			0.77	0.31	0.77	0.32
Number of varieties	13	13	13	13	28	13	28	13

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.4.3 Saskatchewan

With the largest share of observations in the full dataset, Saskatchewan's results are largely similar to the prairie-wide level. As in each of the previous cases, Table 6.5 presents these results, with even numbered models containing *lag yield potential* and *lag variety specificity* as the key regressors. Models (19) and (20) are the pooled OLS regressions, Models (21) and (22) use the Hausman-Taylor IV approach, and Models (23) and (24) rely on the FEF approach. I correct standard errors for heteroskedasticity by clustering on varieties.

As observed in several of the other models, when *lag yield potential* and *lag variety specificity* are the key independent variables, explanatory power of the pooled OLS model is relatively higher. Slower maturity rates and leaf spot resistance show positive relationships with adoption in both pooled OLS models, while increased loose smut tolerance appears to be negatively associated with adoption in Model (19). As in the prairie-wide estimates, both Models (19) and (20) indicate S-shaped variety life cycles. Further, variety yield potential displays a positive relationship with adoption and the significant coefficient on variety specificity a negative relationship, both as expected in the conceptual framework.

Moving to the Hausman-Taylor IV models (i.e., Models (21) and (22)), variety life cycle effects remain significant. However, in contrast to the pooled OLS approach, several disease tolerances display significant coefficients. Estimates in both models indicate that lodging resistance and leaf rust tolerance are assets to varieties, while variety acreage declines with higher loose smut tolerance ratings. Models (21) also presents significant negative relationships between both average yield and stripe rust tolerance, and adoption levels.

Modelling using the FEF approach to examining Saskatchewan producer varietal decisions again supports an S-shaped variety life cycle. Further, both Models (23) and (24) indicate that stripe rust tolerance, loose smut tolerance, and variety head awn are significantly correlated with lower adoption levels at a 10 % significance level. Increased lodging resistance appears to positively impact adoption in both models, while protein content exhibits negative effects in Model (23). Finally, of the yield related traits only the coefficient for average yield is statistically significant, but again oddly negative.

Overall, based on estimates from Model (24) using the FEF approach, paired with *lag yield potential* and *lag variety specificity* as the key independent variables, significant factors in Saskatchewan wheat producer variety decisions include variety stripe rust and loose smut tolerance, lodging resistance, and whether or not a variety has an awned head. Degrees of freedom in provincial modeling for Saskatchewan are relatively less restricted than in the other two provinces but the number of available observations is still much lower than in the prairie-wide analysis. This may be why *lag yield potential* and *lag variety specificity* display more significance in Saskatchewan's pooled OLS models, where fewer regressors are included, retaining more degrees of freedom.

Table 6.4: Saskatchewan provincial estimates

Variables	(19)	(20)	(21)	(22)	(23)		(24)	
	Pooled OLS	Pooled OLS	HT-IV	HT-IV	FEF		FEF	
					Step 1	Step 2	Step 1	Step 2
Dependent variable: acres								
Lag yield potential		4,112 **		668.05			362.58	
		(1,617)		(1,115)			(1,125)	
Lag average yield	883.00		-1,652*		-1,812*			
	(1,483)		(954.02)		(978.15)			
Lag variety specificity		-31,575***		-10,008			-8,288	
		(8,584)		(7,853)			(7,742)	
Lag yield variance	-26.61		127.22		114.45			
	(94.58)		(135.11)		(145.71)			
Age	4,836**	3,469**	5,9958***	5,584***	6,007***		5,718***	
	(1,931)	(1,547)	(2,033)	(2,032)	(2,038)		(2,022)	
Age^2	-29.48**	-20.91**	-45.42***	-42.01***	-46.67***		-43.95***	
	(11.41)	(8.93)	(13.49)	(13.52)	(12.61)		(12.58)	
Age^3	0.05**	0.03**	0.07***	0.07***	0.07***		0.07***	
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)		(0.02)	
Protein	21,980	11,951	-156,047	-145,217	-282,191*		-270,778	
	(41,687)	(38,298)	(147,755)	(146,780)	(163,487)		(168,037)	
Stem rust	-8,948	-5,419	18,406	15,657	-9,129		-18,396	
	(16,787)	(16,026)	(28,341)	(24,755)	(37,595)		(37,833)	
Leaf rust	14,828	11,538	76,943*	74,362*	40,696		41,642	
	(16,573)	(15,214)	(42,739)	(42,319)	(26,349)		(25,165)	
Stripe rust	-9,845	-1,246	-41,738**	-32,132	-48,209**		-38,160*	
	(19,615)	(16,886)	(20,449)	(20,088)	(19,913)		(20,089)	
Loose smut	-25,580**	-15,801	-65,098***	-60,847**	-80,869**		-77,509**	
	(11,662)	(11,028)	(23,578)	(23,984)	(31,266)		(32,064)	
Bunt	-10,175	-5,545	66,088	63,975	62,105		60,587	
	(14,422)	(13,340)	(44,622)	(44,860)	(52,763)		(53,266)	
Leaf spot	59,469**	55,584**	16,320	12,440	29,158		24,922	
	(23,284)	(21,819)	(43,629)	(36,654)	(52,031)		(45,486)	
Fusarium head blight	6,140	-4,657	-20,037	-26,608	-69,542		-79,848	
	(19,144)	(18,879)	(27,373)	(28,914)	(55,732)		(59,450)	
Sprouting	-12,122	-9,623	-6,222	-10,677	8,801		177.42	
	(18,406)	(16,831)	(27,427)	(26,415)	(35,992)		(34,490)	
Lodging	18,894	5,829	95,014***	92,397***	108,429***		107,571***	

	(16,332)	(14,274)	(36,207)	(35,708)	(39,344)		(39,218)	
Height	-21,934	-19,082	-18,148	-18,667	-38,091		-39,187	
	(35,305)	(34,343)	(28,129)	(29,716)	(33,052)		(33,816)	
Head awn	-38,405	-19,440	-205,104	-184,336		-258,962**		-235,501**
	(45,376)	(41,295)	(129,005)	(126,012)		(106,606)		(103,440)
Maturity rate	-28,752**	-20,294*	9020	14,039	10,311		14,875	
	(11,638)	(10,440)	(13,441)	(13,897)	(13,852)		(14,250)	
Test weight	-6,299	-3,941	11,100	9,880	13,986		13,296	
	(10,730)	(9,733)	(13,947)	(13,420)	(14,152)		(14,240)	
Seed weight	6,094	5,563	9,256	8,357	14,927		14,741	
	(8,297)	(7,609)	(13,204)	(12,926)	(13,785)		(13,538)	
Wheat class dummy variables	✓	✓						
Constant	-322,075	-279,768	1,764,569	1,550,633	3,864,118	175,426**	3,687,628	159,533**
	(717,036)	(660,711)	(2,112,913)	(2,072,757)	(2,441,988)	(77,776)	(2,487,165)	(75,847)
Observations	310	310	310	310	310	310	310	310
R^2	0.26	0.33			0.76	0.10	0.75	0.09
Number of varieties	68	68	68	68	68	68	68	68

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.4.4 Summary of provincial results

The above results indicate that factors of variety adoption decisions differ by province. FEF estimates for Alberta in Model (12) suggest significant relationships between adoption and variety stripe rust, loose smut, and bunt tolerances, as well as variety head awn. In contrast, Manitoba's Model (18) results point to stem rust and fusarium head blight tolerance. Yet in both, neither yield potential, nor variety specificity display statistically significant correlations with variety adoption. However, as I note in the preceding discussion, this may be the result of insufficient degrees of freedom. Saskatchewan's empirical results suffer less from degrees of freedom limitations, but both yield related variety characteristics remain statistically insignificant in Model (24). Variety head awn and tolerances to stripe rust, loose smut, and lodging do appear to matter. Interestingly, the signs for the estimated effects of stripe rust and variety head awn in Saskatchewan (negative) differ from Alberta's (positive), suggesting significant differences in the factors of variety decisions between these neighbouring provinces. However, this may simply be the result of statistical limitations. Finally, relative to the prairie-wide results, the estimated effect for fusarium head blight tolerance in Manitoba is the only trait matching in both sign and statistical significance.

6.5 Wheat class results

As is the case with different provinces, it is likely the differences in end uses influence the importance of select variety traits. Take for example, the case of HRS discussed in the final section of chapter five. To be classed as HRS, varieties generally produce higher protein contents, making it plausible that the importance of protein content is diminished when variety decisions within this particular wheat class are examined. Below I discuss the results of empirical analyses at the wheat class level for the three largest (in terms of allocated acreage) wheat classes: HRS, CPS, and durum.

6.5.1 Hard red spring

As the dominant wheat class, HRS varieties account for the largest share of the dataset when split by wheat classes. Table 6.6 provides the empirical results for this level of analysis. It follows the same format as the previous results tables, including two estimated pooled OLS models, two estimated Hausman-Taylor IV models, and two estimated FEF models. Due to the presence of heteroskedasticity, I cluster standard errors on varieties again.

Pooled OLS modeling with the key variables of *lag yield potential* and *lag variety specificity* again provide relatively higher explanatory power. Both models indicate varietal stripe rust tolerance significantly and positively impacts adoption decisions, while varietal height and maturity rates display a negative relationship with varietal acreage. As in the prairie-wide analysis, estimated coefficients for *lag variety specificity* and *lag yield potential* are significant, and have the expected signs. One notable difference from the previous analyses is that the lack of significant support for an S-shaped adoption. As I discuss later, this holds true in Model (30), the preferred FEF estimation.

Hausman-Taylor IV estimates, presented in Models (27) and (28), coincide in terms of significance and sign at a 5% level with the pooled OLS estimates in only two traits: varietal height and variety specificity. However, magnitudes of the coefficients for these traits differ. The only other significant variables for HRS observed with the Hausman-Taylor IV approach are the indicators of the shape of the variety life cycle (i.e., $age,\ age^2$, and age^3). All other variety traits display no statistically significant estimated coefficients.

Turning to the estimated FEF models in Models (29) and (30), I observe higher explanatory power when key variables *lag yield potential* and *lag variety specificity* are included. Estimates of the coefficients on varietal height and fusarium head blight tolerance indicate negative relationships with variety adoption in both models. Model (29) suggests that relatively higher stripe rust tolerance has negative implications for varietal acreage, while Model (30) points to a negative effect for leaf spot resistance and positive effect for loose smut tolerance. Statistically significant estimates for variety yield potential and specificity produce the expected signs on these two variety traits, but the shape of the life cycle is less clear. Model (29) reports significant coefficients for all three degrees of variety age, suggesting an S-shaped adoption path, but Model (30) does not, instead lining up with what is observed in the pooled OLS model (i.e., Model (26)).

Placing the analytical focus on the results of Model (30), variety decisions of Canadian Prairie wheat producers within the HRS wheat class depend on the yield potential, variety specificity, variety heights, and the loose smut, leaf spot, and fusarium head blight tolerances. While more disease traits display significant estimated relationships, results for the HRS wheat class are largely consistent with the prairie-wide results. However, protein content does appear to not be a factor in variety decisions within this class, plausibly supporting the idea that the relative importance of certain traits is impacted by wheat classes. For example, there may be insufficient variability in protein content across varieties within the HRS wheat class, reducing the importance of this trait in decisions between HRS varieties.

Table 6.5: Hard red spring wheat class estimates

Variables	(25)	(26)	(27)	(28)	(29)		(30)	
	Pooled OLS	Pooled OLS	HT-IV	HT-IV	FEF		FEF	
					Step 1	Step 2	Step 1	Step 2
	Dependent variable: acres							
Lag yield potential		3,308**		401.16			3,923***	
		(1,237)		(970.51)			(1,075)	
Lag average yield	-625.34		-1,018		814.32			
	(1,443)		(1,015)		(1,095)			
Lag variety specificity		-54,537***		-19,353**			-47,398***	
		(11,061)		(7,650)			(11,696)	
Lag yield variance	-167.50		140.90		32.64			
	(203.55)		(163.60)		(220.12)			
Age	3,854*	952.67	9,608**	7,783**	7,102*		3,238	
	(2,247)	(1,921)	(3,945)	(3,435)	(3,785)		(3,494)	
Age^2	-26.42	-10.15	-91.97***	-77.85***	-64.43**		-39.46	
	(16.19)	(13.50)	(29.69)	(25.94)	(31.40)		(29.06)	
Age^3	0.05	0.03	0.20***	0.17***	0.13*		0.09	
	(0.04)	(0.03)	(0.06)	(0.06)	(0.07)		(0.06)	
Protein	-44,145	-34,347	-994.64	547.70	-119,618		-64,334	
	(42,613)	(42,085)	(167,015)	(158,678)	(116,205)		(102,847)	
Stripe rust	29,159**	31,101***	-805.77	5,700	-69,230*		-44,720	
	(11,035)	(10,402)	(13,062)	(14,543)	(37,368)		(32,417)	
Loose smut	-2,009	3,566	22,568	22,780	67,350		98,220*	
	(17,208)	(17,102)	(21,004)	(19,924)	(65,361)		(53,530)	
Bunt	-32,275	-27,558	-27,123	-26,507	1,854		-5,607	
	(21,313)	(19,211)	(24,964)	(24,130)	(50,478)		(38,286)	
Leaf spot	10,601	3,685	-34,959	-32,107	-128,823		-128,758*	
	(31,931)	(28,690)	(28,274)	(26,280)	(103,063)		(72,223)	
Fusarium head blight	13,994	1141.8	-23,300	-24,833	-175,228***		-146,279**	
	(22,804)	(21,775)	(30,845)	(29,466)	(56,155)		(61,838)	
Sprouting	-1,422	138.11	8,123	4,547	19,152		17,973	
	(13,998)	(13,325)	(20,406)	(18,870)	(98,116)		(81,330)	
Lodging	-2,620	-18,242	49,612	39,758	50,727		22,164	
	(20,068)	(20,984)	(43,393)	(40,119)	(40,607)		(30,482)	
Height	-114,631***	-89,605***	-78,863***	-69,525***	-131,301***		-85,154***	
	(32,297)	(27,386)	(27,653)	(24,969)	(39,634)		(30,680)	
Head awn	-18,724	-6.18	-30,770	-10,714		21,007		62,533
	(43,910)	(41,132)	(84,713)	(84,488)		(85,685)		(75,043)

Maturity rate	-23,347**	-19,839*	15,934	19,046	-1,103		10,685	
	(9,269)	(10,595)	(15,934)	(16,154)	(15,242)		(15,950)	
Provincial dummy variables	✓	✓	✓	✓	✓		✓	
Constant	1,045,874	899,286	108,739	95,733	2,525,531	-10,402	1,497,478	-34,085
	(646,464)	(636,114)	(2,596,408)	(2,433,107)	(1,628,241)	(58,655)	(1,480,556)	(53,514)
Observations	378	378	378	378	380	378	380	378
R^2	0.22	0.33			0.51	0.00	0.58	0.02
Number of varieties	47	47	47	47	47	47	47	47

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.5.2 Canada Prairie spring

A smaller wheat class than HRS, CPS varieties on average yield higher than HRS varieties but face increased protein content volatility, as seen in Table 5.5. Below, Table 6.7 provides estimation results for variety decisions within the CPS wheat class. In line with the other tables in this chapter, Models (31) and (32) are the pooled OLS approach, (33) and (34) are the Hausman-Taylor IV approach, and (35) and (36) reflect FEF estimates. I again correct for heteroskedasticity using clustered standard errors.

Few variety traits show statistical significance as factors in the pooled OLS models for the CPS class. With relatively better explanatory power, Model (32) indicates that *lag variety specificity* is significantly (at the 10% level) and negatively associated with adoption of CPS varieties. Additionally, *lag yield potential* and variety height show positive associations with adoption in this model. Model (31) shows a similar positive correlation between variety height and variety adoption within this class.

Hausman-Taylor IV estimates find no significance of any of the yield related variety traits. However, an S-shaped patter for variety life cycles is supported by these results. Sprouting resistance also appears to be a positively contributing factor in variety adoption decisions.

In contrast, estimates of the favoured FEF approach used in Models (35) and (36) point to several additional significant factors, although with differences between the two. Model (35), finds significant positive associations between variety loose smut tolerance and oddly, variety height. This last observation suggests that taller CPS varieties are more widely used within the portion of acres allocated to this wheat class by producers across the prairie provinces and holds for Model (36) as well. Factors with significant coefficients in Model (36) include the variety specificity (negative in sign as expected), variety head awn, lodging resistance, and tolerance to fusarium head blight.

In short, looking at the results of Model (36), adoption intensity levels for CPS wheat varieties seem to depend on varietal height, fusarium head blight tolerance, variety head awn, and lodging resistance. Further, the estimated coefficient for a variety's adaptability (i.e., inverse of variety specificity) shows significant correlations with variety acreage. Protein content is not significantly correlated with adoption levels in any of the CPS models but the positive estimated effects of variety heights are interesting, as in general, such varieties face increased susceptibility to lodging. However, this result may be the product of reduced degrees of freedom due to the small number of observations for the CPS class and large number of regressors.

Table 6.6: Canada Prairie spring wheat class estimates

Variables	(31)	(32)	(33)	(34)	(35) FEF		(36) FEF	
	Pooled OLS	Pooled OLS	HT-IV	HT-IV	Step 1	Step 2	Step 1	Step 2
Dependent variable: acres								
Lag yield potential		1,727*		-247.28			678.10	
		(957.26)		(465.78)			(1,112)	
Lag average yield	446.23		-766.34		-271.37			
	(990.59)		(599.43)		(1,252)			
Lag variety specificity		-10,828*		-794.61			-7,673*	
		(5,228)		(1,519)			(3,519)	
Lag yield variance	-69.02		17.44		-18.39			
	(6.01)		(27.30)		(33.61)			
Age	1,084	976.44	-3,299**	-3,245**	-1,475		-1,750	
	(3,758)	(3,525)	(1,504)	(1,445)	(3,088)		(2,512)	
Age^2	-9.21	-10.67	33.25**	34.13**	20.48		24.04	
	(34.80)	(32.40)	(14.81)	(14.66)	(27.15)		(23.18)	
Age^3	0.03	0.03	-0.11***	-0.11***	-0.08		-0.09	
	(0.08)	(0.08)	(0.04)	(0.04)	(0.07)		(0.06)	
Protein	-46,664	-50,562	45,920	47,449	-33,400		-27,536	
	(29,460)	(29,356)	(29,987)	(36,305)	(22,817)		(18,006)	
Stripe rust	-3,863	-6,539	1,116	-2,666	-10,246		-32,681	
	(13,906)	(11,997)	(36,614)	(31,562)	(37,765)		(25,527)	
Loose smut	31,703	30,266	20,506	27,983	70,653**		22,683	
	(29,325)	(27,832)	(37,999)	(35,227)	(25,701)		(18,509)	
Bunt	28,599	34,188	-18,758	-22,636	-45,382		-	
	(26,017)	(23,421)	(22,436)	(22,311)	(29,991)			
Leaf spot	27,047	12,981	-28,603	-27,627		-216,645		-91,824
	(26,402)	(27,839)	(61,357)	(58,659)		(134,063)		(106,119)
Fusarium head blight	26,916	22,281	-56,918	-55,134	-		-72,118**	
	(24,104)	(22,156)	(36,583)	(37,471)			(28,998)	
Sprouting	-14,069	-32,297	52,295**	45,152**	-105,801		-114,119	
	(40,303)	(40,558)	(23,108)	(18,862)	(99,942)		(83,017)	
Lodging	20,850	30,606	13,565	11,395	-39,493		-35,554*	
	(45,213)	(43,156)	(14,365)	(15,250)	(27,051)		(16,630)	
Height	35,083*	25,308*	4,174	5,303	51,052***		42,742***	
	(17,480)	(13,671)	(17,738)	(18,196)	(16,074)		(9,551)	
Head awn	-55,946	-81,004	47,730	42,827		-96,676		-235,313**
	(63,303)	(63,977)	(64,965)	(64,901)		(103,183)		(93,916)

Maturity rate	7,509	15,495	-2,172	-1,495	-1,186		1,171	
	(25,821)	(27,289)	(10,715)	(12,561)	(20,622)		(18,866)	
Provincial dummy variables	✓	✓	✓	✓	✓		✓	
Constant	168,323	263,892	-445,706	-464,834	904,353**	670,579	1,035,533***	449,936
	(437,644)	(445,628)	(438,468)	(513,970)	(318,936)	(402,188)	(138,653)	(318,356)
Observations	67	67	67	67	67	67	67	67
R^2	0.43	0.50			0.82	0.19	0.85	0.17
Number of varieties	12	12	12	12	12	12	12	12

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.5.3 Durum

Wheat class level estimates for durum varieties, presented in Table 6.8, differ from the other two examined wheat classes, particularly in the signs of estimated effects of some disease tolerances (i.e., bunt, loose smut, and leaf spot). The format of the table remains the same, containing two pooled OLS, two Hausman-Taylor IV, and two FEF regressions. As in all other analyses in this chapter, I correct standard errors through clustering on varieties.

In the pooled OLS models, explanatory power is again higher when *lag yield potential* and *lag variety specificity* form the key independent variables. Slower maturity rates, taller varieties, and improved sprouting and bunt resistance display significant (at the 5% level) associations with variety adoption in both Models (37) and (38). Relatively higher fusarium head blight tolerance is negatively related to variety adoption levels according to both pooled OLS models. All indicators of the variety life cycle show significance, supporting an S-shaped adoption path for varieties in both models, while protein content displays a positive association with acreage in Model (37). Across the key independent variables, coefficients for both *lag average yield* and *lag yield potential* are positive in their respective models. Further, variety specificity has the expected negative sign, significant at the 10% level in Model (38). But the pooled OLS estimates remain subject to bias by leaving variety specific effects unaddressed.

The Hausman-Taylor IV model, which accounts for these variety effects with the help of several assumptions produces different results from the first two models in Table 6.8. While coefficients on maturity rates, variety heights and bunt tolerance in both Models (39) and (40) remain consistent with the results of the pooled OLS models, the effect of sprouting resistance is now estimated as negative. Further, several other disease tolerances (i.e., lodging, leaf spot, and stripe rust) show significant and positive associations with adoption levels. Loose smut maintains its negative sign and support for the S-shape life cycle of varieties continues. However, none of estimated coefficients for the yield based varietal traits display significance.

Moving to the FEF estimates in Models (41) and (42), this lack of significance for the yield related variety traits continues. However, I still observe significant coefficients for maturity rates, leaf spot tolerance, and bunt tolerance, although magnitudes differ with each empirical approach. Fusarium head blight resistance, variety height and loose smut resistance also remain significant factors based on these estimated models.

Focusing on the results of Model (42) which uses the preferred empirical approach and includes the main variety trait of interest, variety specificity, it appears that several traits factor into durum classed variety decisions. These include variety maturity rates, variety heights, and bunt, leaf spot, fusarium head blight, and loose smut tolerances. From the results of this particular model, variety specificity exhibits no association with variety acreage. However, observations are again limited for this level of analysis, reducing the degrees of freedom in all models and in particular, for the panel approaches that include variety specific effects.

Table 6.7: Durum wheat class estimates

Variables	(37) Pooled OLS	(38) Pooled OLS	(39) HT-IV	(40) HT-IV	(41) FEF Step 1	(41) FEF Step 2	(42) FEF Step 1	(42) FEF Step 2
	Dependent variable: acres							
Lag yield potential		5,587**		-1,342			-1,085	
		(2,004)		(1,244)			(950.94)	
Lag average yield	5,804*		-2,181		-2,297			
	(3,124)		(1,846)		(1,709)			
Lag variety specificity		-34,847*		-3,291			133.82	
		(16,410)		(10,230)			(10,161)	
Lag yield variance	-195.57		-54.51		78.73			
	(348.08)		(327.38)		(315.27)			
Age	17,323**	16,871**	14,244***	14,840***	14,649**		15,085**	
	(6,476)	(5,847)	(4,727)	(5,085)	(5,482)		(5,626)	
Age^2	-117.62**	-116.95***	-79.28***	-83.58***	-88.14**		-90.34**	
	(41.26)	(37.21)	(22.69)	(24.58)	(30.91)		(30.42)	
Age^3	0.18**	0.18***	0.11***	0.12***	0.12**		0.13**	
	(0.06)	(0.06)	(0.03)	(0.03)	(0.04)		(0.04)	
Protein	243,908*	171,914	289,941	290,325	-74,082		-43,057	
	(134,733)	(134,013)	(177,621)	(185,927)	(158,162)		(175,447)	
Stripe rust	-190,133	-106,057	94,273**	91,089**	19,624		12,910	
	(122,937)	(113,652)	(42,262)	(43,398)	(73,615)		(76,888)	
Loose smut	521.01	5,639	-51,709**	-47,648**	-66,553**		-63,067*	
	(33,495)	(30,940)	(20,307)	(19,345)	(27,699)		(27,298)	
Bunt	306,710***	280,376***	338,235***	333,736***	212,994***		210,120***	
	(85,394)	(79,846)	(33,847)	(35,752)	(68,623)		(69,794)	
Leaf spot	-151,500	-118,647	235,266**	224,188**	195,979*		182,997*	
	(155,684)	(126,286)	(91,967)	(87,824)	(116,274)		(116,143)	
Fusarium head blight	-231,997*	-285,836**	-183,282	-186,806		-418,921***		-400,919***
	(122,380)	(124,452)	(163,990)	(156,458)		(121,499)		(118,347)
Sprouting	188,533**	145,653**	-123,600*	-122,024*	-8,198		-1,362	
	(72,952)	(60,539)	(70,692)	(70,832)	(83,005)		(82,274)	
Lodging	-20,559	-33,717	141,820*	133,648*	154,919		147,717	
	(42,654)	(42,696)	(79,907)	(74,502)	(92,374)		(89,081)	
Height	737,875**	724,007**	232,026*	259,615*		566,125***		568,295***
	(325,289)	(281,236)	(152,846)	(155,443)		(86,046)		(85,142)
Head awn	-	-				-		-

Maturity rate	-106,126**	-80,780**	-49,918***	-53,187**	-50,368**		-54,613*	
	(42,126)	(37,488)	(18,842)	(21,951)	(24,925)		(26,476)	
Wheat class dummy variables	✓	✓	✓	✓	✓		✓	
Constant	-6,449,957***	-5,455,753***	-7,284,081**	-7,316,307**	-997,741	-1,095,388**	-1,414,961	-1,129,955**
	(1,948,308)	(1,971,364)	(2,898,628)	(3,040,609)	(2,101,095)	(396,178)	(2,421,683)	(389,885)
Observations	74	74	74	74	81	74	81	74
R^2	0.65	0.68			0.89	0.70	0.89	0.70
Number of varieties	15	15	15	15	15	15	15	15

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.5.4 Summary of wheat class results

Results at the wheat class level of analysis suggest variety adoption factors vary by class. FEF estimates for HRS varieties in Model (30) are largely consistent with prairie-wide results, with yield potential, variety specificity, variety heights, and fusarium head blight tolerance maintaining significance. Differences include the insignificance of protein content, replaced by significant effects for loose smut and leaf spot tolerances. Further, some key differences are observable between HRS results and those from CPS and durum class modeling, although the latter two models are subject reduced degrees of freedom. In CPS's Model (36), estimated effects for yield potential and leaf spot tolerance are now insignificant. However, variety head awn and fusarium head blight tolerance are negatively associated with variety adoption within the CPS class and the estimated effect for variety height is positive. This positive association is also observed in the empirical results for the durum wheat class. Additional significant factors for this class include bunt, leaf spot, and loose smut tolerances, as well as variety maturity rates.

6.6 Discussion of overall findings

In this section, I summarize the main findings of the empirical estimates and discuss the possible explanations and implications. This discussion focuses primarily on the findings and implications of Model (6), the estimated FEF model at the prairie-wide level that includes yield potential and variety specificity as independent variables. I focus on these estimates for four reasons:

(1) the FEF approach has advantageous statistical properties in the context of variety adoption empirical modeling;
(2) the prairie-wide dataset provides the largest degrees of freedom which results in more reliable estimates;
(3) explanatory power is higher in Model (6) than in Model (5), indicating that the pairing of yield potential and variety specificity explains more of the variations in acreage across varieties, when compared to using average yield and the yield variance; and
(4) this model examines the relationship between variety adoption and varietal adaptability (measured as the variety specificity), one of the main aims of this research.

Based on estimates in Model (6), five varietal traits are significant factors in variety decisions of Canadian Prairie wheat producers. These are varietal height, protein content, fusarium head blight tolerance, yield potential, and adaptability (or specificity).

The estimated FEF coefficient for varietal height is negative and significant at the 10% significance level. Recall that I measure heights on a four-point scale, where a value of four indicates a relatively taller variety. Based on the estimated sign, taller wheat varieties are less desirable to Western Canadian wheat producers, with the model predicting that on average, a one unit increase in the relative height of a variety is associated with an approximately 57,000 acre decline in its allocated acreage. Since the height of a variety factors into its lodging resistance, with semi-dwarf varieties facing reduced susceptibility (Kelbert et al., 2004), this negative association between variety height and adoption lines up with expectations. This result is also consistent with the pooled OLS result in Table 6.2 that includes *lag variety specificity* (i.e., Model (2)) in terms of sign and a 10% significance level, although the magnitude of the correlation differs. Further, all alternative models in Appendix D report a negative and significant relationship between variety height and adoption levels at the prairie-wide level of analysis (i.e., Models (D2), (D4), and (D6)). In fact, even when I relax the minimum risk area constraint, variety height remains significantly, negatively associated with variety adoption levels across the Canadian Prairies.[39]

Examining the importance of variety height at provincial and wheat class levels produces different results. In the corresponding models at these secondary analysis levels (i.e., Models (12), (18), (24), (30), (36), and (42)), it appears that varietal height matters most for HRS and CPS varieties. However, in the case of the latter wheat class, taller varieties appear more widely used. This is an odd result given the negative implications of heights for other variety traits, but may stem from a lack of adequate degrees of freedom.

An important factor of end use value, I expect advantages in relative protein content increase the desirability of a wheat variety. However, Model (6) suggests that this relationship is actually negative. At a 5% significance level, the estimated FEF empirical model finds a 1 percentage point increase in the protein content of the average variety corresponds to a decline of

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[39] Results for the full dataset, without the minimum requirement of four risk areas of data in a given year and province, are available in Appendix C.

approximately 125,000 acres. In other words, if the average acreage per variety is roughly 137,000 acres (as is the case for the subset of varieties with complete observations and meeting the minimum risk area requirement) a variety with a protein content 1 percentage point higher than the average across all varieties is predicted to achieve only 10% of the average acreage (i.e., 14,000 acres). However, it is worth noting that a 1 percentage point increase in protein content between varieties is relatively high, with protein contents falling between 13-15 percentage points for 68% of varieties in the sample.

It is plausible that the observed negative association between a variety's protein and adoption levels is the product of a trade-off between protein content and variety yield. Evidence of such a trade-off is found by Iqbal et al. (2007), where higher yielding varieties typically provide lower protein contents. Comparing these FEF results with all other fixed effects-based models (i.e., the fixed effects Tobit and two-way fixed effects approaches), even when the minimum risk area requirement is lifted, protein maintains a negative relationship with variety adoption. Pooled OLS, Hausman-Taylor IV, and Tobit modelling results differ, finding no significant effect of protein content. However, as I discuss in the previous chapter, these models are subject to bias and limitations which may explain these differing results.

In contrast, provincial and wheat class level analyses generally find no significant effect of varietal protein content. One possible explanation comes from the statistical power of these levels of analysis. With reduced observations in each set of models, there may not be sufficient degrees of freedom available, resulting in diminished power of these empirical models to estimate variety adoption.

Fusarium head blight is the only significant estimated coefficient for disease tolerances in Model (6). Measured on a five-point scale, where higher values indicate better tolerance, I expect to find a positive relationship between this disease tolerance and variety adoption. However, the estimated coefficient for fusarium head blight tolerance when yield variations are measured using variety specificity is negative. From Model (6), it appears that on average, a one unit increase in a variety's tolerance to fusarium head blight corresponds to a roughly 121,000 acre decrease in its adoption. Although the magnitudes, and in some cases significance, differ, this empirical result is consistent in sign across most of the other models estimated using *lag variety specificity* as one of the independent variables and the subset of data that meets the minimum risk area requirement (i.e., Models (2), (4), (D2), (D4), and (D6)). Overall, this result suggests that, *ceteris paribus*, wheat varieties with relatively higher tolerance to fusarium head blight are less widely adopted by wheat producers in the Canadian Prairies. One possible explanation for this is that, like protein content, some trade-off with another desired varietal trait exists, but which trait this may be is unclear. If such trade-offs exist, this estimated negative relationship between variety adoption and fusarium head blight tolerance may stem from the fact that current mitigation strategies recommend the integrated use of fungicides, crop rotation, and cultivar resistance in combating this particular disease, and not cultivar resistance alone (Ye et al., 2017). Revisiting Table 5.3, the average variety within the dataset has a resistance (or tolerance) rating of two, indicating relatively marginal resistance. If there is a trade-off between fusarium head blight tolerance and another desirable varietal trait, this low average resistance rating for fusarium head blight may push farmers to prioritize the other trait. Alternatively, it may be that over the entire span of the dataset, fusarium head blight resistance was less important in some periods, making any trade-off not worth it. Therefore, results may differ if focusing on a time period after significant outbreaks. Section 6.7 revisits these possible explanations for this unexpected empirical result.

At provincial and wheat class levels, the estimated effect of fusarium head blight shows significance in Manitoba and for each of the three wheat class models. Fusarium head blight is more likely to be found in black soil zones, of which Manitoba's allocated wheat acreage largely is (Clear & Patrick, 2010). However, the model again indicates a negative correlation between fusarium head blight and variety adoption within the province of Manitoba. Similarly, modeling at the HRS, CPS, and durum levels again produce negative relationships between these two variables.

The predicted relationship between variety adoption and yield potential is, as I expect, highly significant at the 1% significance level and positive. Assuming that farmers gauge expected yields based on these yield potentials, this positive link with variety adoption makes sense. In selecting varieties that are more likely to yield higher, the wheat producer increases their expected yield and therefore, potential profits. Model (6) points to an additional bushel per acre in yield potential from the average variety corresponding with an increase of over 3,000 acres allocated to it. This estimate is slightly lower in magnitude than the coefficient for yield potential estimated by the pooled OLS approach (i.e., Model (2)), but as the FEF accounts for variety specific heterogeneity while the pooled OLS does not, the difference is likely the result of omitted variable bias in Model (2). While the Hausman-Taylor IV approach reflects no significant correlation, variety yield potential maintains a significant, positive estimated relationship with variety adoption in all other empirical approach at the prairie-wide level.

Reviewing the results of FEF modeling relying on variety specificity and yield potential for varietal yield indicators at the provincial and wheat class levels of analysis, a significant correlation between yield potential and variety adoption is only observed for HRS varieties. One possible conclusion is that yield potential is less important in CPS and durum variety selection. However, given the comparatively smaller degrees of freedom available in empirical modeling for these two classes, it is more plausibly the case that the insignificance of these estimated yield potential coefficients is due to limited statistical power.

As expected, empirical results indicate that more adaptable varieties are more widely adopted. Recall from chapter three that the degree of variety specificity (i.e., the mathematical inverse of adaptability) is the slope of the yield curve, reflecting the rate of change in yield (i.e., change in bushels per location or acre in this context) as the area allocated to variety *i* expands beyond the optimal location. From the estimated coefficient in Model (6), it appears that on average, a one-bushel decline in variety specificity corresponds to a more than 30,000 acre increase in variety adoption. That is, improving the adaptability of a variety such that the average loss in yield is reduced by one bushel as area expands from the best yielding location to the second-best location, and so on, correlates with an expansion in allocated acreage to approximately 122% for the average variety acreage. This significant link between the adaptability and adoption of varieties may at least partially explain the phenomenon observed in Figure 4.5, where a handful of varieties dominate each provincial market. Further, as climate change continues to escalate the volatility in growing conditions for wheat producers across the Canadian Prairies, I expect this varietal adaptability will become increasingly important as a means of reducing some of the risks they face.

This significant, negative (positive) correlation between variety specificity (adaptability) and variety adoption levels is consistent across results for the alternative empirical approaches when a minimum requirement of four risk areas of data is imposed. Comparing this result to provincial and wheat class level FEF estimates, only HRS and CPS results report a significant estimate. When analysis is done at the provincial level, or for the durum wheat class, I find no significant link between variety specificity and adoption. However, this may stem from a shortage of available degrees of freedom, limiting the power of the FEF model to estimate accurate coefficients on variety traits.

In addition to showing a strong association between variety adoption levels and varietal adaptability in the main model (i.e., Model (6)), the empirical results support the idea that variety specificity better captures varietal adaptability, relative to using yield variance. Comparing Models (5) and (6) for the clearest example of this, the explanatory power when yield potential and variety specificity form the key independent variables is approximately 4% higher than when using average yield and yield variance. Further, neither of the estimated effects for average yield and yield variance in Model (5) are significant, while both yield potential and variety specificity show the expected strong positive and negative respective correlations with adoption. Across the provincial and wheat class level results, models relying on yield potential and variety specificity perform at least as well as those relying on average yield and yield variance in all but one case (Saskatchewan). In capturing the interaction of several seed traits and land, it is shown that wheat variety specificity does serve as a better indicator of adaptability than yield variance, which focuses on changes over time.

As Table 6.9 summarizes, provincial and wheat class level analyses point to additional factors in variety decisions, some of which I discuss in the previous section of this chapter. For example, a variety's lodging resistance appears to matter to producers in Saskatchewan but this trait is not significant in any other analysis level. However, as I have previously mentioned, many of these empirical models face reduced statistical power due to reduced observations leading to a small number of available degrees of freedom. Therefore, the most reliable results are that of the prairie-wide level analysis but some of these models provide additional insights that should be explored further if more data is obtained.

One final thing to note is that, by using risk area level data across the Canadian Prairies instead of farm level data (which was unavailable for this thesis), the results above are general. This may explain why some varietal trait effects appear insignificant or have unexpected estimated signs, as it is plausible that certain varietal traits matter only in select regions. Take for example, fusarium head blight, which favours humid conditions. Producers in regions that typically face such conditions more regularly likely place an increased weight on a variety's tolerance to this disease. However, because this study looks at the overall insured acreage across three provinces such significant regional preferences are lost in the aggregate estimates.

Table 6.9: Significant factors of variety adoption and signs based on FEF estimates with *lag yield potential* and *lag variety specificity* as key independent variables (for significance level of 10%)

Variables	Prairies	Alberta	Manitoba	Saskatchewan	Hard red spring	Canada Prairie spring	Durum
Lag yield potential	+				+		
Lag variety specificity	–				–	–	
Age	+	+		+			+
Age^2	–	–	–	–			–
Age^3	+		+	+			+
Protein	–						
Stem rust	.	.	–		.	.	.
Leaf rust	.	.			.	.	.
Stripe rust		+		–			
Loose smut		+		–	+		–
Bunt		–				.	+
Leaf spot					–		+
Fusarium head blight	–		–		–	–	–
Sprouting							
Lodging				+		–	
Height	–				–	+	+
Head awn		+		–		–	
Maturity rate							–

. indicates variable not included in FEF model estimation

6.7 Discussion of unexpected results for select disease tolerances

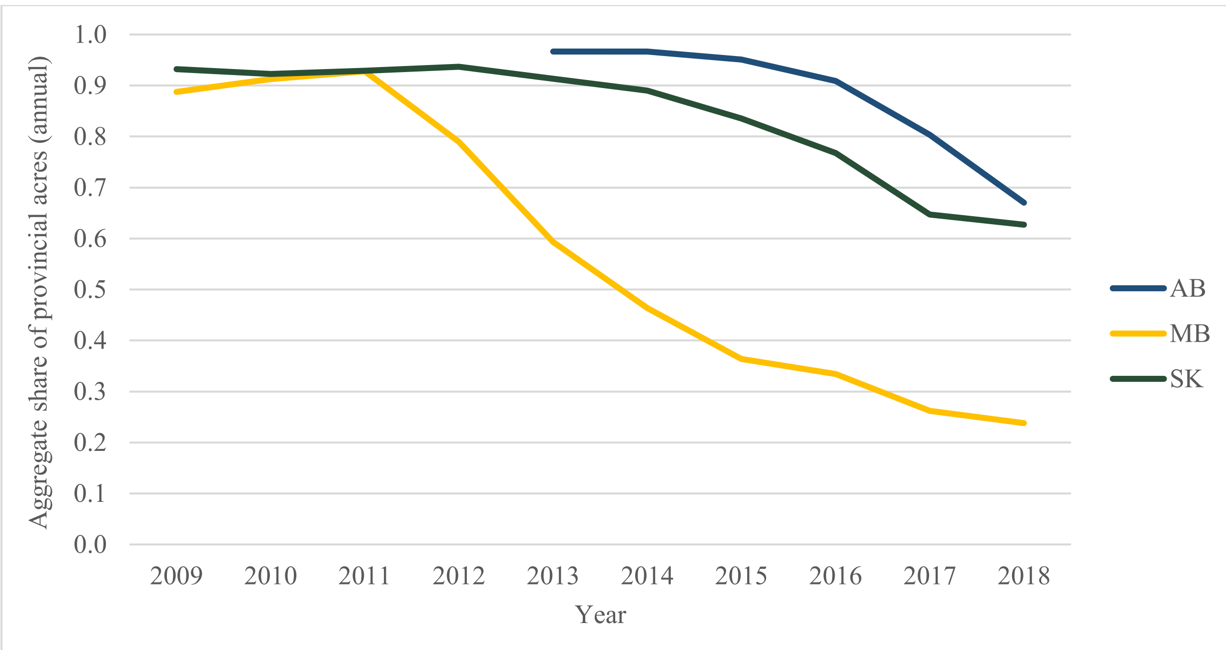
Estimated effects in Model (6) for several disease tolerances such as bunt, fusarium head blight, and leaf spot, as well as for other variety traits like protein content, lodging resistance, and maturity rates are either insignificant or in some cases opposite in sign from expectations. However, there is a strong correlation between variety yields and these traits. Improved traits like higher disease tolerances ratings both increase the yield potential of a variety, and are more likely to be bred into higher yielding varietal lines to begin with. The combination of this multi-collinearity between *lag yield potential* and several of these varietal traits and the slow changing nature of the ratings used to measure such traits may be what is causing these different results, as most of the variability is captured in the yield term effect and obtaining a true *ceteris paribus* effect for each trait is challenging. With this in mind, I take a deeper look into the trends in shares of provincial acres for varieties with higher fusarium head blight tolerance.

As I discuss in the preceding section of this chapter, the estimated coefficient for fusarium head blight differs from expectations at the prairie-wide level. Reducing the risk of grain spoilage due to this disease, and thereby improving the yield potential, varieties with higher tolerance for (or resistance to) fusarium head blight should be more desirable to producers, particularly in regions where outbreaks are prevalent. As a result, I would expect a positive association between variety tolerance to fusarium head blight and adoption levels. In contrast, prairie-wide level modeling indicates a negative association.

While I offer a possible trade-off argument in the previous section, here I take a more detailed look at the data in order to gain a better understanding of trends in the adoption of varieties with improved fusarium head blight tolerance that the empirical models may not be picking up. Figure 6.1 shows the trend in the aggregate share of provincial acres allocated to varieties with lower fusarium head blight tolerance. The decline in overall provincial shares of acreage for these varieties is notable, with the steepest decline beginning around 2011 in Manitoba. A corresponding increase in the proportion of provincial acreages allocated to varieties with fusarium head blight tolerance ratings of at least four is observable in Figure 6.2. This apparent shift from lower tolerance rated varieties to those more resistant to fusarium head blight is what I expected to find, especially in Manitoba. While this disease has gradually spread across the prairie provinces, it is most frequently problematic in black soil zones, of which Manitoba's acreage allocated to wheat production largely is (Clear & Patrick, 2010). Therefore, varieties with relatively higher fusarium head blight tolerance should be more widely adopted, particularly in Manitoba.

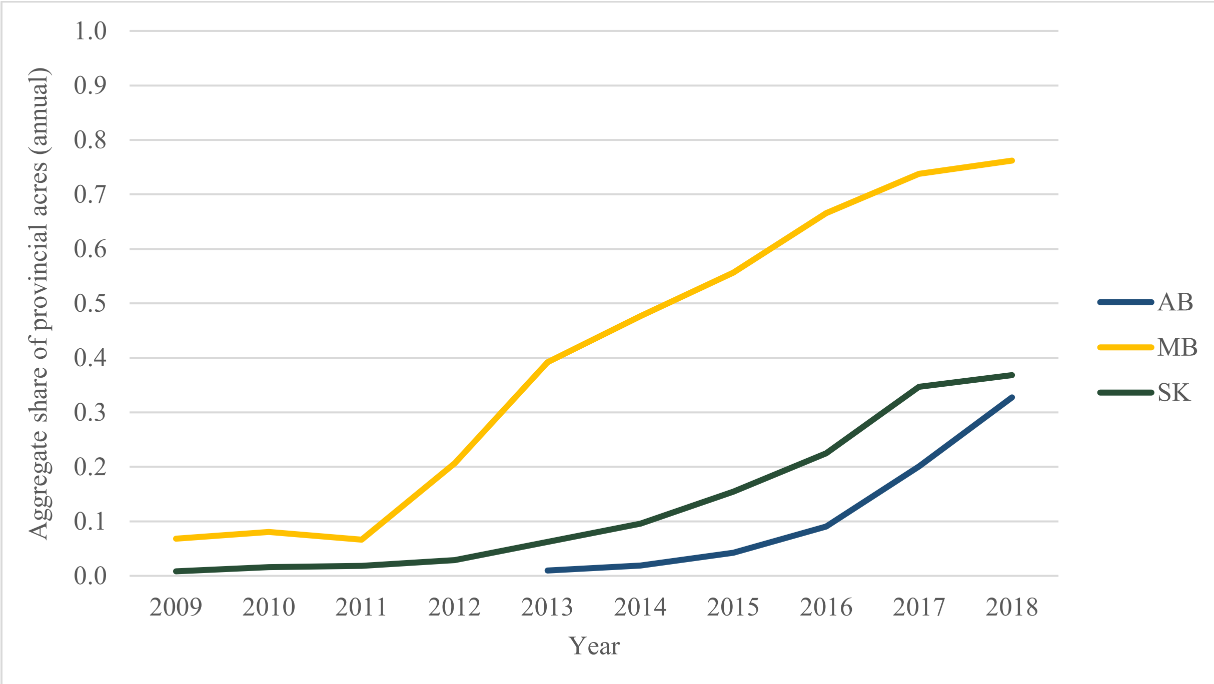
What exactly is causing this divergence between the empirical estimates and the behavioural pattern shifts observed in Figures 6.1 and 6.2 remains unclear. However, one possibility is that most of the variation is picked up through the estimated effect for yield potential, as I discuss above. Alternatively, it may result from a lack of sufficient variation in fusarium head blight ratings over time within varieties. Fusarium head blight tolerance ratings are slow to change within a variety, generally only shifting from one rating to the next as information about the relative performance of a variety is updated over time (Kirk, 2020b). Often these changes occur once within the 10-year span of the data, making fusarium head blight tolerance a slow changing variable. This data limitation impacts the ability of the FEF to accurately estimate its effect and may be why a negative correlation with adoption is observed in the empirical models.

Figure 6.1: Trends in aggregate shares of provincial acres of low fusarium head blight tolerance rated varieties (rated 1, 2, or 3)



Sources: Agriculture Financial Services Corporation (n.d.), Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agricultural Services Corporation (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.), Saskatchewan Crop Insurance Corporation (n.d.), Saskatchewan Seed Growers' Association (n.d.)

Figure 6.2: Trends in aggregate share of provincial acres of high fusarium head blight tolerance rated varieties (rated 4 or 5)

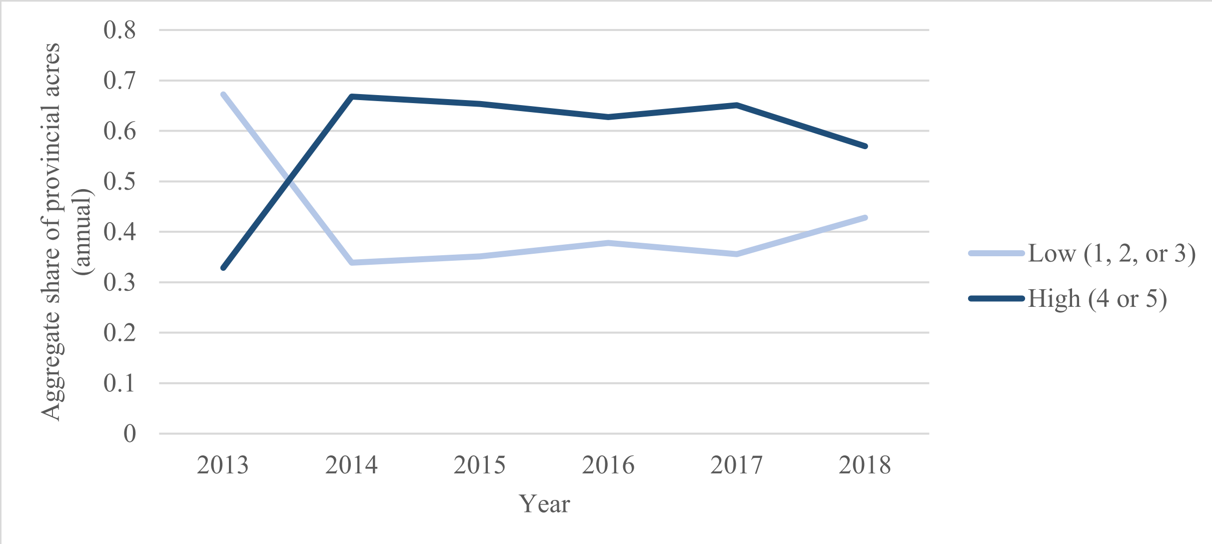


Sources: Agriculture Financial Services Corporation (n.d.), Alberta Seed Growers & Alberta Seed Processors (n.d.), Manitoba Agricultural Services Corporation (n.d.), Manitoba Agriculture and Resource Development, Manitoba Seed Growers' Association, & the Manitoba Co-operator (n.d.), Saskatchewan Crop Insurance Corporation (n.d.), Saskatchewan Seed Growers' Association (n.d.)

Another unexpected result is the negative estimated coefficient for varietal bunt tolerance, alternatively referred to as common bunt tolerance, in Alberta's analysis. Historically, this disease has caused significant yield losses across much of the world (Aboukhaddour et al., 2020). However, Aboukhaddour et al. (2020) note that bunt outbreaks in wheat across Western Canada have been relatively low since the mid 20th century thanks to the development and use of resistant cultivars and fungicides. Canada is one of few countries that continues to prioritize breeding for resistance to bunt, with Aboukhaddour et al. (2020) suggesting that the rise in the popularity of organic production has spurred additional interest in the continued improvement of variety resistance to this disease. As a result, I expected to find a positive relationship between variety adoption levels and higher resistance to bunt. Prairie-wide level analysis suggest there is no significant correlation between resistance to this disease and variety adoption decisions, which could be explained by the reduced prevalence of this disease in recent years or by the correlation between a variety's common bunt tolerance and its yield potential. However, Alberta's estimated negative relationship between these two variables remains unexpected.

Looking at the available data for Alberta, there is a visible one-time shift towards varieties with relatively higher bunt tolerance (Figure 6.3). As a result, I again observe a divergence between the estimated empirical effect and the trend in aggregate shares of provincial acreage towards more bunt tolerant varieties. There are several possible explanations for this different result. One possible explanation that I note earlier in this chapter is that it may stem from a trade-off between varietal bunt tolerance and another more desired varietal trait for Albertan wheat producers. Alternatively, given that the main shift seems to occur in a single year, it could be that some event in 2013 pushed farmers towards varieties with higher bunt tolerance (e.g., an outbreak in common bunt in Alberta). Another possibility is that it stems from limited variations in bunt tolerance ratings within varieties over the available time period. Finally, it may be that there are insufficient degrees of freedom at this level of analysis, impacting the accuracy of the empirical estimates. If it is limited degrees of freedom generating this divergence between the estimated results and expected relationship between adoption and this varietal disease, then using an interaction term between bunt tolerance and Alberta in the prairie-wide level analysis may offer more reliable empirical results for the importance of this trait to Albertan wheat producers.

Figure 6.3: Trends in aggregate share of Alberta's provincial acres of for high and low bunt tolerance rated varieties



Sources: Agriculture Financial Services Corporation (n.d.), & Alberta Seed Growers & Alberta Seed Processors (n.d.)

Chapter 7: Conclusion

7.1 Introduction

This chapter summarizes the conclusions of this thesis and the resulting implications. It begins with a summary of the objective and empirical approach, followed by an overview of the main findings. A discussion of the implications of these findings and a look at some of the key limitations follows. The chapter concludes with some areas of potential future research.

7.2 Thesis summary

The main aim of this thesis is to empirically examine which traits drive wheat variety adoption decisions in the Canadian Prairies, with a focus on the relationship between the adaptability of a new variety and its adoption. To do this, I first develop a conceptual framework based on Hotelling's (1929) horizontal differentiation model to explore the relationship between adoption and varietal adaptability. Then, using risk area level data spanning from 2009 to 2018 and Pesaran and Zhou's (2018) panel data fixed effects filter (FEF) econometric model, I estimate the effects of agronomic traits and end-use value indicators on wheat variety adoption at the prairie-wide, provincial, and wheat class levels.

Results from the econometric analysis indicate that producers across the Prairies are concerned with varietal height, protein content, fusarium head blight tolerance, yield potential, and adaptability (measured by the degree of variety specificity). Consistent with expectations, taller varieties show negative relationships with adoption. This negative association plausibly reflects the trade-off between varietal height and susceptibility to lodging, as I discuss in more detail in chapter six. Empirical results show strong positive associations between adoption levels and varieties with relatively higher yield potential and improved adaptability. For the latter, the estimated coefficient for variety specificity indicates that for this sample, improving the adaptability of a variety by 1 bushel corresponds to an over 30,000 acre increase in adoption of the variety on average. That is, decreasing the rate of decline in yield as area expands beyond the optimal location for a variety correlates with an increase in how widely a variety is adopted. These results suggest that varieties with comparative advantages in potential yields and those more adaptable to various growing conditions achieve higher adoption rates. Further, the explanatory power is higher for models relying on yield potential and variety specificity than for those using average yield and yield variance, suggesting that variety specificity is a better measure of adaptability in this setting. Lifecycle indicators support an S-shaped adoption pattern for wheat varieties, with the initially rapid adoption rates decreasing and then turning negative as varieties near the end of their lifecycle. Counter to expectations, varieties with higher protein content and those better resistant to fusarium head blight show negative relationships with adoption. As I discuss in the previous chapter, it is plausible that these negative relationships reflect either trade-offs with other varietal traits (e.g., Iqbal et al. (2007) find some evidence of such a trade-off existing between protein content and yields) or data limitations (i.e., strong correlations with yield potential and challenges associated with modeling slow changing variables). Figures 6.1 and 6.2 reveal a clear shift towards varieties with higher tolerance ratings, suggesting that this latter explanation may be why empirical modeling results counter intuition. Finally, provincial and wheat class level analyses produce slight variations from these results, but limited available data impedes the ability to obtain more accurate estimates at these levels.

In addition to these insights into the key factors of wheat variety decisions in the Canadian Prairies, there are two empirical modeling related findings. First, as previously mentioned, modeling using yield potential and variety specificity as variety yield indicators performs better for this sample in terms of explanatory power, relative to using average yield and yield variance. Second, FEF modeling results in higher explanatory power of the model than the pooled OLS approach for this sample, while maintaining the ability to estimate time invariant trait effects.

7.3 Implications

Insights into Canadian Prairie wheat producer variety decisions gained from these results may be used by both public and private players in the early stages of the Canadian wheat supply chain to:

(1) help inform the allocation of resources to breeding programs that target variety traits most important to producers; and

(2) aid in ensuring producers have access to the information they need when selecting varieties.

Ensuring that current wheat research priorities align with the needs of producers is critical to improving the efficiency of breeding programs, and insights gained from this thesis provide additional information that may be helpful in these decisions. Though I cannot assign causality, correlations between some varietal characteristics and adoption suggest that prioritizing breeding programs focused on improving these attributes may be beneficial. For example, the strong association observed between variety adaptability and adoption suggests that the overall success of a variety is linked to how widely or narrowly adaptable it is (i.e., its degree of specificity). Therefore, prioritizing breeding programs which aim to improve the wide adaptability of varieties may be beneficial to Canada's wheat industry. This finding aligns with a recent report by Agriculture and Agri-Food Canada and Cereals Canada (2020) that identifies improved wheat yield reliability as a research priority, with a goal of enhancing yield stability under variable climate conditions (i.e., adaptability). However, as Roy and Kharkwal (2004) note, developing varieties with certain traits for specific needs and areas may remain important and necessary as well. Finding the right balance between breeding for specific and for wider ranges of growing conditions is key, though challenging and subject to changes over time.

Providing Canadian wheat producers with convenient access to accurate and complete information on new wheat varieties assists them in making fully informed decisions. Such information is available in provincial Seed Guides and Yield Magazines; however, a measure of varietal adaptability is not currently reported. This leaves it up to farmers to undertake the calculation of some form of yield stability under varying climates themselves, a time-consuming endeavour. In light of the findings of this thesis regarding the relationship between varietal adaptability and variety adoption, developing an intuitive indicator of how well a variety is able to adapt to a range of growing conditions and including this in such publications along side other variety data could be beneficial to Western Canada's wheat industry. Particularly, by including an intuitive measure of adaptability along side other yield related information for each variety in provincial Yield Magazines, farmers will be better equipped to make the best varietal decisions for their operations, even as climate change continues to increase the volatility in growing conditions that these producers face.

In addition to these two implications, and related to the latter, this research provides a look at some of the challenges associated with access to data. As I discuss in more detail in chapter four, obtaining reliable, consistent, and representative data across the three Prairie Provinces is extremely difficult. This in turn complicates research efforts aimed at identifying the challenges that Western Canadian wheat farmers face and limits the ability of farmers to analyze all of this variety data at seeding time. Making the data as accessible as possible to farmers is important, particularly as climate change adds to the factors that they must consider when deciding between wheat varieties. More readily available data gives farmers the tools needed to compare varietal characteristics such as yields, adaptability, and disease tolerances more easily. Further, increasing the both the accessibility and consistency of data across Western Canada allows for more efficient and effective research.

Several stakeholders in the Canadian wheat supply chain stand to potentially benefit from the information garnered from this research, with the most direct benefits going to breeders and government agencies involved in wheat research and development. Added information on which variety characteristics correlate with higher adoption rates makes it easier for them to ensure that they are targeting the right attributes. While the impacts of most breeding decisions today will not be realized for another 12-15 years (Alston et al., 1995; Agriculture and Agri-Food Canada, 2013a; Agriculture and Agri-Food Canada 2013b), changing climates and corresponding increases in extreme weather events mean it is likely that factors such as varietal adaptability will only increase in importance.

In addition, this information may be useful in trial design and reporting decisions. Even though most Canadian wheat producers use farm saved seeds, results of this thesis reflect information on all insured acreage decisions (where sufficient data is reported), regardless of whether production seeds were purchased or saved. Therefore, it may be helpful in evaluating potential updates to trial reports for the producers who do choose to purchase certified seeds, as well as in improving marketing of new varieties to those who typically choose to use farm saved seeds.

Finally, these insights may be indirectly beneficial to both Western Canadian wheat producers and the overall economy through realized benefits resulting from the improved allocation of resources within the early stages of the Canadian wheat supply chain.

7.4 Limitations

Limited data availability is one of the key limitations of this study. Not all data for insured acreage across Alberta, Manitoba, and Saskatchewan between 2009 and 2018 is available. Also unavailable are farm level observations. By alternatively using risk area level data across the Canadian Prairies, some insights into individual farmers' variety preferences are lost.

Another limitation is the endogenous nature of some variables. Calculations for both variety specificity and yield variance rely on the number of risk areas in which a variety is reported for a given province and year. As a result, the values of both of these variables depend on adoption, and are therefore endogenous, limiting the interpretations of the coefficient estimates to those of correlation. However, this approach is inline with that of Barkley and Porter (1996), who include yield variance in their adoption model for Kansas wheat producers. With no obviously strong instrumental variables available, I use variety specificity and yield variance to understand the relationships between these measurements of yield volatility and adoption but note the limitation that no causal relationship can be established without first addressing this endogeneity.

7.5 Future research

This thesis does not explicitly look at the role that seed distributors play in Western Canadian wheat variety adoption. As the agents between breeders and farmers, it is plausible that the decisions of these seed distributors impact farmer variety choices since they are the ones providing the certified seed to the local farmers who choose to purchase each year. However, in the absence of adequate farm level data, empirically identifying this influence is challenging. If such data becomes available, further research on the role of these intermediary agents in the wheat supply chain is needed to understand the extent of this influence on which new varieties are successfully adopted by wheat producers.

Additionally, it may be beneficial to consider trial yields as opposed to realized yields collected from Yield Magazines. Trial yields published in provincial Seed Guides reflect long term yield data from various test sites (Kirk, 2020b). Particularly for newer varieties with less available realized yield data, these trial yields provide additional information that farmers likely considered when deciding between varieties. Comparing these trial yields with realized yields may provide further insights into Western Canadian wheat varietal decisions.

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Appendix A

Table A.1: Hausman-Taylor model regressors and possible endogeneity with respect to the variety specific effects

Independent variable	Exogenous (x_{1it}, z_{1i})/ endogenous (x_{2it}, z_{2i})*	Reasoning
Lag yield potential	x_{2it}	Yield depends on both observed and unobserved variety specific traits. Traits such as sawfly tolerance are both specific to the variety and potentially significantly impact variety yield potential.[40]
Lag average yield	x_{2it}	Yield depends on both observed and unobserved variety specific traits. Traits such as sawfly tolerance are both specific to the variety and potentially significantly impact variety yield potential.
Lag variety specificity	x_{2it}	The degree of variety specificity is a function of the number of risk areas a variety is insured in, as well as the maximum and minimum yields. Since these yields are assumed endogenous, variety specificity is also likely endogenous with respect to the variety specific attributes.
Lag yield variance	x_{2it}	Yield variance is a function of the number of risk areas a variety is insured in, as well as the sum of the deviations from the mean yield. Since these yields are assumed endogenous, yield variance is also likely endogenous with respect to variety specific attributes.
Life cycle (age, age^2, age^3)	x_{1it}	The lifecycle itself could be endogenous as the speed at which a variety is adopted and disadopted is a function of its specific attributes, some of which may be unobservable. However, the age of a variety is exogenously determined and this is used to capture variety lifecycles in the models. In a sense, age to the third-degree polynomial acts as an IV for variety lifecycle.
Protein	x_{2it}	Protein content is influences by seed colour, texture, and whether a variety is spring or winter wheat (Schuh, 2020). Dummy variables for wheat classes to control for these unobserved trait effects on protein are not included in the Hausman-Taylor IV model, as they are also correlated with variety effects. Therefore, protein content is assumed endogenous.
Stem rust	z_{1i}	Stem rust favours excess moisture and moderate to high temperatures (Duveiller et al., 2012). As a result, maturity timing and variety nutrient uptake efficiency could impact variety susceptibility. However, the inclusion of maturity and variety specificity as regressors allow for the assumption of stem rust resistance exogeneity.
Leaf rust	z_{1i}	Leaf rust favours excess moisture and moderate to high temperatures (Duveiller et al., 2012). As a result, maturity timing and variety nutrient uptake efficiency could impact variety susceptibility. However, the inclusion of maturity and variety specificity as regressors allow for the assumption of leaf rust resistance exogeneity.
Stripe rust	z_{1i}	Stripe rust favours excess moisture and cooler temperatures (Duveiller et al., 2012). As a result, maturity timing and variety nutrient uptake efficiency could impact variety susceptibility. However, the inclusion of maturity and variety specificity as regressors allow for the assumption of stripe rust resistance exogeneity.

[40] Yield potential is measured as the maximum observed yield for a variety within a province and year in this thesis. Measured in this manner, the yield potential is not exogenous to variety specific effects.

Loose smut	z_{1i}	Loose smut favours cooler, humid planting conditions (Duveiller et al., 2012). As a result, maturity rates could impact variety susceptibility where slower maturing varieties are planted earlier and more likely to face such conditions. However, the inclusion of maturity as a regressor allows for the assumption of loose smut resistance exogeneity.
Bunt	z_{1i}	Bunt favours cooler germination stage temperatures (Duveiller et al., 2012). As a result, maturity rates could impact variety susceptibility where slower maturing varieties are planted earlier and more likely to face such conditions. However, the inclusion of maturity as a regressor allows for the assumption of loose smut resistance exogeneity.
Leaf spot	z_{1i}	Leaf spot favours a wide range of temperatures and long periods of excess moisture (Duveiller et al., 2012). As a result, maturity timing and the interaction between genotype and land (i.e., variety specificity) potentially influence variety susceptibility. However, the inclusion of maturity and variety specificity as regressors allow for the assumption of leaf spot resistance exogeneity.
Fusarium head blight	z_{1i}	Fusarium head blight favours humid conditions and moderate to high temperatures (Duveiller et al., 2012). As a result, maturity timing and variety nutrient uptake efficiency could impact variety susceptibility. However, the inclusion of maturity and variety specificity as regressors allow for the assumption of fusarium head blight resistance exogeneity.
Sprouting	z_{1i}	Sprouting, referring to pre-harvest sprouting, favours humid conditions in later stages (Mohan et al., 2009). As a result, maturity timing could impact variety susceptibility. However, the inclusion of maturity as a regressor allows for the assumption of sprouting resistance exogeneity.
Lodging	z_{1i}	Lodging tolerance depends on plant height and root and stalk structures (Kelbert et al., 2004). As a result, variety height and nutrient uptake efficiency could impact variety susceptibility. However, the inclusion of height and variety specificity as regressors allows for the assumption of lodging tolerance.
Height	z_{1i}	Variety height depends on nutrient uptake efficiency, with both of these factors impacting lodging tolerance (Kelbert et al., 2004). Including variety specificity as a regressor allows for the assumption of variety height exogeneity.
Head awn	z_{1i}	Head awn is built into the genetic code of a variety; the variety either has an awned head or not. Therefore, head awn is assumed exogenous.
Maturity rate	z_{1i}	Variety nutrient uptake efficiency could influence the observed maturity rate of a variety. Including variety specificity as a regressor allows for the assumption of maturity rate exogeneity.
Test weight	z_{1i}	Test weight depends in part on variety disease resistance (Duveiller et al., 2012). While several of these are included in the models, some lesser diseases do not have available data. As a result, test weight is assumed endogenous for the Hausman-Taylor IV models.
Seed weight	z_{1i}	Seed weight should be largely determined by genetics and impacts variety decisions by influencing the seeding rate. It is also generally positively correlated with test weight and therefore included to prevent endogeneity of test weight (Gray, 2021). It is assumed exogenous.

* x_{jit} where $j = 1,2$ indicate the regressors that vary over time, z_{ji} indicate the regressors that are time invariant

Nutrient uptake efficiency rates are intrinsic to the genotype, differing across varieties (Chanda et al., 2011). These can affect other traits of the variety, such as the lodging susceptibility, protein content, yield, and disease tolerance due to their impacts on the overall health of plant (i.e., plants lacking sufficient nutrition have lower yields and weaker tolerances for diseases). A variety's adaptability measures this interaction of the genotype with the growing conditions it faces (e.g., soil nutrients, weather patterns, etc.) and therefore should capture the intrinsic ability of a variety to adapt to its growing environment. I include this adaptability in the models via *lag variety specificity* and *lag yield variance*, the latter believed a less accurate measure. By doing so, the effect of nutrient uptake efficiency is removed from the variety specific effect γ_i, and the z_i's that are impacted by this factor are no longer endogenous with respect to γ_i.

Finally, the assumption here is that if a fixed variety trait is not reported in the seed guide, it is not an important factor in variety decisions and therefore should not have a significant correlation with any of the observed variety traits. This does not mean that no unobserved time invariant traits impact the observed time invariant traits, but that there is unlikely to be a significant correlation due to the relative importance of the trait in farmer variety selection. Any believed to significantly impact other traits are already included in the model, as noted in Table A.1.

While I make a case in support of each of these exogeneity and endogeneity assumptions, it is plausible that at least some of these do not hold. Alternatively, assuming that most variety traits are endogenous results in a lack of available exogenous variables to serve as IVs in the Hausman-Taylor IV model. Unfortunately, these assumptions are the key limitation of using the Hausman-Taylor IV model. The FEF model's advantage is that for the Prairie-wide level analysis, only variety head awn requires an orthogonality assumption. Since a variety either has the genetics to produce a bearded head or it does not, this assumption comes with a fair degree of confidence.

Appendix B

Table B.1: Table of time invariant regressors for all levels (Prairie, provincial, and wheat class)

Independent variable	Prairies	AB	MB	SK	HRS	CPS	Durum
Stem rust		-				✓	✓
Leaf rust		-	✓			✓	-
Stripe rust							
Loose smut		✓	✓				
Bunt							
Leaf spot			✓			✓	
Fusarium head blight		✓					✓
Sprouting*		✓					
Lodging			✓				
Height		✓					✓
Head awn	✓	✓	✓	✓	✓	✓	-
Maturity rate			✓				
Test weight	-		-		-	-	-
Seed weight	-		✓		-	-	-

(-) denotes variables omitted from the sets of slowly changing and time invariant variables

* sprouting is time invariant in Alberta when the restriction of a minimum of four risk areas is imposed

Appendix C

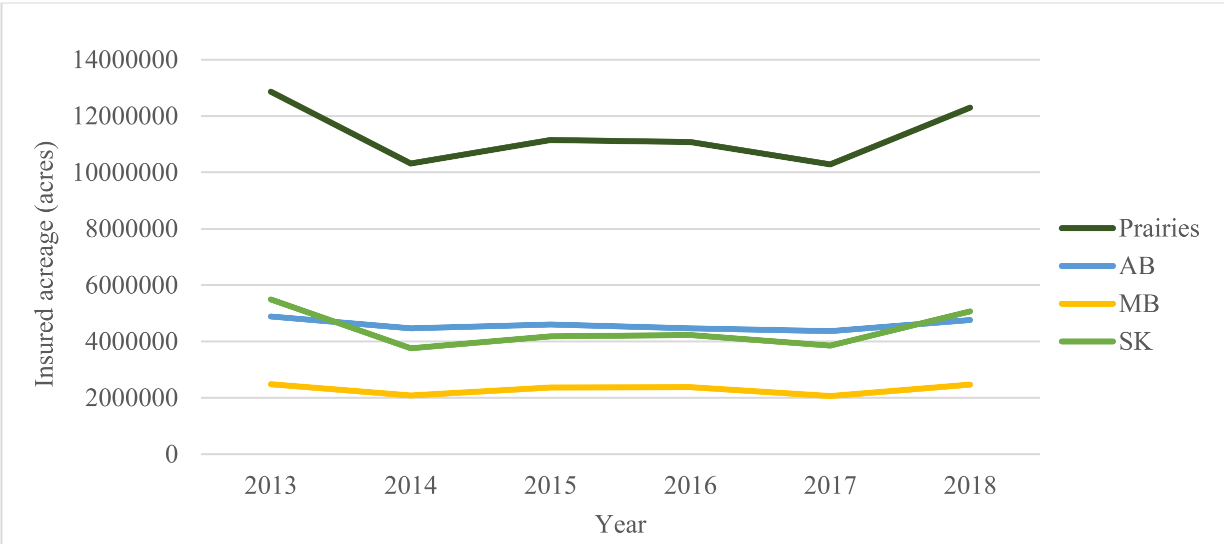
Within the fixed effects portion of the FEF models, the possible presence of systematic differences over time presents a potential for omitted variable bias. These effects impact the dependent variable but do not differ in effect across cross-sections (Baltagi, 2005). In the context of wheat variety adoption, potential causes of such differences are:

(1) persistent upwards or downwards linear trends in overall acreage, or
(2) one-time shocks in growing or economic conditions (e.g., drought, flood, disease outbreak, etc.).

As shown in Figures C.1 and C.2, neither are apparent over the time frame considered. Even so, given another setting (e.g., longer time period) where these effects are visibly present, inclusion of a time trend variable controls for the former issue (Baltagi, 2005). To address the latter issue, using a two-way fixed effects approach instead of the FEF captures both variety and time fixed effects. However, this two-way approach is most commonly used in causal effect models with only two time periods, not ten, as is the case here. This complicates interpretations of these time effects within the context of wheat variety adoption. Further, even if time fixed effects capture a poor weather event or economic year, farmers rarely know with certainty what type of season they face at the time of selecting a variety and insuring their acreage. When they do, there is no need to insure acres against uncertainty. Since I use insured acres as the dependent variable, it appears unlikely that the time fixed effects reveal much about farmer variety decisions, except in the case where a one-time event becomes more frequent. Then farmers may shift their behaviour to varieties more tolerant to such an event (e.g., consistent increases in fusarium head blight prevalence causing a shift to varieties with higher resistance ratings).

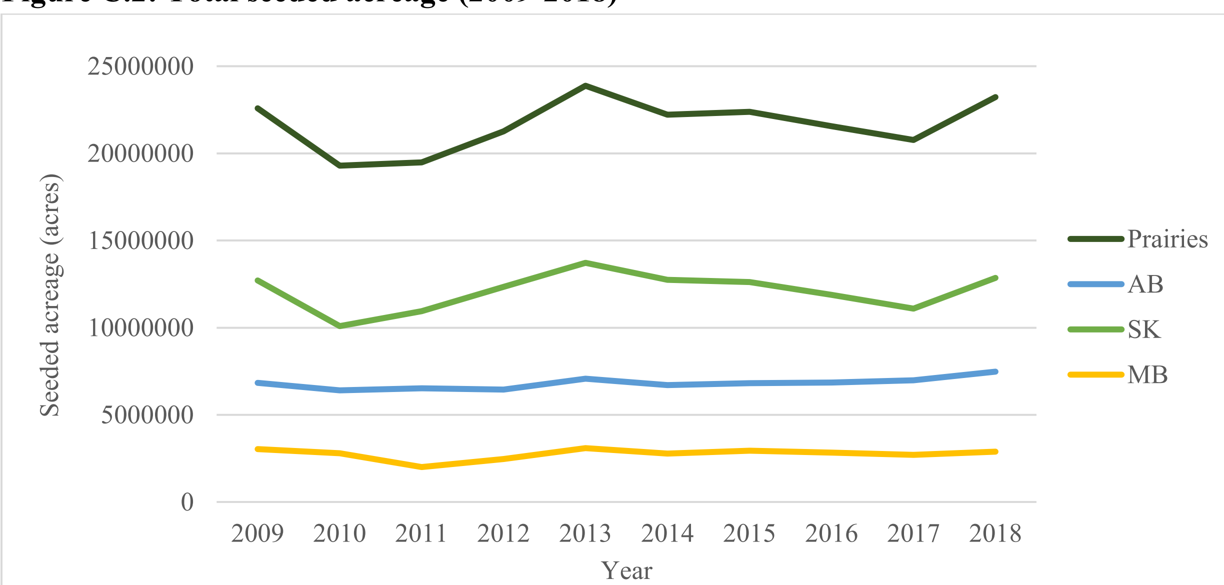
The combination of unclear interpretations with lack of severe shocks or visible trends in total insured and seeded acreage at either the provincial or prairie-wide levels supports using the one-way fixed effects model. However, testing suggests statistical differences between time effects when included in the model. Paired with a possibility of a trend in disease intensity, some support for the inclusion of time fixed effects exists. With these considerations in mind, I include estimates of the two-way fixed effects model at the prairie-wide level in Appendix D, but the primary analysis of focuses on the one-way fixed effects model within Pesaran and Zhou's (2018) FEF model.

Figure C.1: Total insured wheat acreage in the full dataset (2013-2018)



Sources: Saskatchewan Crop Insurance Corporation (n.d.), Agriculture Financial Services Corporation (n.d.), Manitoba Agricultural Services Corporation (n.d.)

Figure C.2: Total seeded acreage (2009-2018)



Source: Statistics Canada (n.d.a)

Appendix D

Appendix D contains results tables for comparison of the results presented in chapter six. Tables D.1 to D.7 display estimates for the alternative econometric approaches not included in chapter six (i.e., Tobit, fixed effects Tobit, and two-way fixed effects models) at each analyses level where a minimum of four risk areas of data within a year and province is required. Tables D.8 to D.14 present estimated results using the full dataset (i.e., no minimum risk area requirement).

Table D.1: Prairie-wide estimates using alternative econometric approaches

Variables	(D1) Tobit	(D2) Tobit	(D3) Fixed effects Tobit	(D4) Fixed effects Tobit	(D5) Two-way fixed effects	(D6) Two-way fixed effects
Dependent variable:	share				acres	
Lag yield potential		0.13***		0.10***		6,018***
		(0.04)		(0.03)		(1,585)
Lag average yield	0.01		0.00		2,362	
	(0.04)		(0.04)		(1,735)	
Lag variety specificity		-1.99***		-1.46***		-35,029***
		(0.20)		(0.19)		(9,267)
Lag yield variance	-0.01**		-0.00		36.01	
	(0.00)		(0.00)		(149.88)	
Age	0.06*	-0.02	0.12***	0.04	6,205	4,446
	(0.04)	(0.04)	(0.04)	(0.04)	(5,388)	(4,504)
Age^2	-0.00	0.00	-0.00***	-0.00**	-39.50***	-26.88**
	(0.00)	(0.00)	(0.00)	(0.00)	(14.41)	(12.37)
Age^3	0.00	-0.00	0.00***	0.00*	0.06***	0.05**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)
Protein	0.11	-0.71	-4.45***	-3.67***	-161,764*	-138,216**
	(0.71)	(0.67)	(1.22)	(1.16)	(76,995)	(59,141)
Stripe rust	0.42	0.64**	-1.71**	-1.13*	-60,084	-43,329
	(0.31)	(0.29)	(0.70)	(0.67)	(41,445)	(34,350)
Loose smut	-0.34	-0.09	-2.60**	-2.41**	-26,510	-23,245
	(0.32)	(0.30)	(1.10)	(1.05)	(43,529)	(37,813)
Bunt	-0.95***	-0.88***	0.59	0.43	46,013	36,059
	(0.28)	(0.26)	(0.82)	(0.79)	(45,272)	(41,990)
Leaf spot	1.24**	0.92*	-1.69	-2.72**	-2,823	-29,381
	(0.51)	(0.47)	(1.39)	(1.33)	(79,342)	(65,046)
Fusarium head blight	-0.01	-0.41	-10.21***	-10.03***	-128,041**	-128,075**
	(0.36)	(0.34)	(2.86)	(2.66)	(53,258)	(53,064)
Sprouting	-0.19	-0.29	0.31	0.38	-27,061	-9,746
	(0.33)	(0.31)	(1.52)	(1.45)	(75,271)	(64,135)
Lodging	1.26***	0.70	1.29	1.09	35,117	23,291
	(0.52)	(0.50)	(0.88)	(0.85)	(34,929)	(29,215)
Height	-2.71***	-2.09***	-2.89***	-2.04**	-80,171*	-54,875*
	(0.71)	(0.67)	(0.82)	(0.79)	(41,419)	(30,280)
Head awn	1.12	1.59*	-1.24	0.52		
	(0.95)	(0.88)	(2.89)	(2.76)		
Maturity rate	-1.12***	-0.78*	-0.58	-0.17	-22,296	-15,388

	(0.43)	(0.40)	(0.49)	(0.47)	(22,681)	(22,375)
Provincial dummy variables	✓	✓	✓	✓	✓	✓
Wheat class dummy variables	✓	✓				
var(*share*)	39.62***	33.63***	23.17***	20.85***		
	(2.76)	(2.32)	(1.60)	(1.43)		
Constant	3.33	15.14	127.40***	112.25***	2,969,956**	2,480,281***
	(12.07)	(11.42)	(23.98)	(22.84)	(1,215,379)	(929,583)
Observations	529	529	529	529	538	538
R^2					0.53	0.59

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.2: Alberta estimates using alternative econometric approaches

Variables	(D7) Tobit	(D8) Tobit	(D9) Fixed effects Tobit	(D10) Fixed effects Tobit	(D11) Two-way fixed effects	(D12) Two-way fixed effects
Dependent variable:			share		acres	
Lag yield potential		0.10*		-0.00		641.78
		(0.05)		(0.03)		(1,862)
Lag average yield	0.02		0.00		274.23	
	(0.07)		(0.03)		(2,888)	
Lag variety specificity		-0.99***		-0.00		-5,392
		(0.22)		(0.13)		(5,976)
Lag yield variance	-0.00		0.00		86.04	
	(0.00)		(0.00)		(63.20)	
Age	0.17	0.14	0.14**	0.14*	7,460**	7,061**
	(0.12)	(0.11)	(0.07)	(0.07)	(3,635)	(3,407)
Age^2	-0.00	-0.00	-0.00*	-0.00	-46.36	-41.46
	(0.00)	(0.00)	(0.00)	(0.00)	(27.61)	(25.45)
Age^3	0.00	0.00	0.00	0.00	0.05	0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.06)
Protein	-1.24	-1.92	0.08	0.53	-50,654	-71,251
	(1.55)	(1.39)	(2.06)	(2.03)	(58,313)	(65,904)
Stripe rust	1.63***	1.59***	1.14*	1.24*	20,829	23,574
	(0.44)	(0.40)	(0.66)	(0.68)	(14,227)	(16,357)
Loose smut	2.35***	2.10***	2.24	2.13		
	(0.49)	(0.45)	(193.00)	(196.02)		
Bunt	0.11	0.05	-0.59	-0.93	-278,684***	-282,143***
	(0.45)	(0.40)	(55.15)	(56.02)	(36,301)	(35,604)
Leaf spot	-2.13**	-1.98**	-6.17	-5.82	-	-
	(0.94)	(0.87)	(55.15)	(56.02)		
Fusarium head blight	-0.54	0.10	-1.79	-1.98		
	(0.57)	(0.54)	(275.69)	(280.01)		
Sprouting****	-0.19	-0.19				
	(0.50)	(0.46)				
Lodging	-1.32	-2.82**	0.64	0.39	-3,721	-16,786
	(1.28)	(1.22)	(1.98)	(2.04)	(23,353)	(20,243)
Height	-4.60**	-4.35***	-2.51	-3.44		
	(1.74)	(1.59)	(539.26)	(547.56)		
Head awn	0.56	0.08	1.81	1.51		
	(1.63)	(1.50)	(512.39)	(519.66)		
Maturity rate	3.98***	3.25**	1.66	1.74	42,561	53,408

	(1.38)	(1.26)	(2.12)	(2.17)	(91,723)	(79,304)
Test weight	0.62	0.57	-0.36	-0.18	-19,758	-18,353
	(0.58)	(0.54)	(0.68)	(0.69)	(18,053)	(15,911)
Seed weight	-0.03	-0.01	0.45	0.36	20,321	24,376
	(0.32)	(0.29)	(1.01)	(1.02)	(31,201)	(25,454)
Wheat class dummy variables	✓	✓				
var(*share*)	12.56***	10.40***	1.91***	1.96***		
	(1.99)	(1.64)	(0.30)	(0.31)		
Constant	-27.33	-10.52	4.83	-4.58	1,748,229	1,792,326
	(44.37)	(40.36)	(1,248.05)	(1,268.98)	(1,604,732)	(1,341,189)
Observations	103	103	103	103	114	114
R^2					0.93	0.93

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**** sprouting is time invariant in Alberta when the restriction of a minimum of four risk areas is imposed

Table D.3: Manitoba estimates using alternative econometric approaches

Variables	(D13) Tobit	(D14) Tobit	(D15) Fixed effects Tobit	(D16) Fixed effects Tobit	(D17) Two-way fixed effects	(D18) Two-way fixed effects
Dependent variable:		share			acres	
Lag yield potential		-0.10		-0.06*		-6,979
		(0.07)		(0.04)		(5,178)
Lag average yield	-0.16**		-0.03		-10,740*	
	(0.07)		(0.03)		(6,161)	
Lag variety specificity		-1.46***		-0.83***		-22,918
		(0.52)		(0.27)		(16,724)
Lag yield variance	-0.01		-0.02***		-245.48	
	(0.01)		(0.00)		(222.84)	
Age	-0.20**	-0.21**	0.00	0.00	6,868	7,125
	(0.09)	(0.09)	(0.04)	(0.04)	(4,825)	(4,718)
Age^2	0.00	0.00	-0.00***	-0.00***	-69.02*	-62.87*
	(0.00)	(0.00)	(0.00)	(0.00)	(35.98)	(32.18)
Age^3	-0.00	-0.00	0.00***	0.00***	0.16*	0.15*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.07)
Protein	5.01	5.70*	3.29	3.64*	352,281	357,371
	(3.30)	(3.17)	(2.14)	(2.05)	(289,644)	(277,959)
Stem rust	-11.85***	-10.21***	-7.37***	-7.00***	-269,996*	-294,256***
	(3.60)	(3.43)	(2.17)	(2.09)	(135,570)	(99,723)
Leaf rust	1.13	0.21	-6.73	-10.64*		
	(3.46)	(3.27)	(6.00)	(5.95)		
Stripe rust	1.65	0.69	1.55	1.19	84,467	62,472
	(2.03)	(1.90)	(1.26)	(1.21)	(56,198)	(41,670)
Loose smut	-6.67***	-6.16***	9.71***	9.43***		
	(1.89)	(1.83)	(1.47)	(1.42)		
Bunt	3.25**	1.93	-2.64***	-2.56***	-57,097	-23,708
	(1.31)	(1.33)	(0.82)	(0.79)	(60,707)	(56,184)
Leaf spot	-20.80***	-18.84***	18.65***	16.82**		
	(5.18)	(5.15)	(6.63)	(6.40)		
Fusarium head blight	0.16	0.35	-12.26***	-11.36***	-196,438***	-128,816**
	(2.90)	(2.67)	(1.81)	(1.80)	(36,788)	(62,410)
Sprouting	-3.59***	-3.28***	7.65***	8.98***	102,328**	94,851*
	(1.17)	(1.11)	(1.48)	(1.50)	(46,850)	(52,720)
Lodging	-0.11	-0.34	2.02	-0.03		
	(1.77)	(1.75)	(4.59)	(4.47)		
Height	-1.74	-0.84	0.53	0.35	-57,383	-114,585

	(1.45)	(1.42)	(0.71)	(0.69)	(149,945)	(166,334)
Head awn	-37.68***	-34.18***	10.39	10.12		
	(8.62)	(8.53)	(7.79)	(7.45)		
Maturity rate	-30.39***	-26.32***				
	(5.41)	(5.67)				
Seed weight	-12.91**	-12.21**	-4.01	-10.02		
	(5.35)	(5.00)	(9.84)	(9.69)		
Wheat class dummy variables	✓	✓				
var(*share*)	11.85***	11.18***	2.42***	2.30***		
	(2.13)	(2.00)	(0.43)	(0.41)		
Constant	204.00**	175.99**	-48.57	-20.82	-2,921,836	-3,105,153
	(78.65)	(76.08)	(56.01)	(56.19)	(3,880,030)	(3,750,890)
Observations	67	67	67	67	118	118
R^2					0.40	0.42

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.4: Saskatchewan estimates using alternative econometric approaches

Variables	(D19) Tobit	(D20) Tobit	(D21) Fixed effects Tobit	(D22) Fixed effects Tobit	(D23) Two-way fixed effects	(D24) Two-way fixed effects
Dependent Variable:			share		acres	
Lag yield potential		0.15***		0.04*		3,127**
		(0.03)		(0.02)		(1,565)
Lag average yield	0.04		-0.02		677.49	
	(0.04)		(0.03)		(1,389)	
Lag variety specificity		-1.29***		-0.48***		-13,320*
		(0.19)		(0.13)		(7,851)
Lag yield variance	-0.00		0.00		73.29	
	(0.01)		(0.00)		(158.99)	
Age	0.15***	0.09***	0.20***	0.18***	6,723***	6,003***
	(0.03)	(0.03)	(0.02)	(0.03)	(2,456)	(2,253)
Age^2	-0.00***	-0.00***	-0.00***	-0.00***	-50.59***	-45.58***
	(0.00)	(0.00)	(0.00)	(0.00)	(13.85)	(12.76)
Age^3	0.00***	0.00**	0.00***	0.00***	0.08***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)
Protein	0.16	-0.26	-6.17***	-5.75***	-360,848***	-360,357***
	(0.64)	(0.61)	(1.60)	(1.56)	(135,440)	(119,908)
Stem rust	-0.36	-0.20	-2.19	-2.35	-27,398	-33,658
	(0.49)	(0.45)	(1.90)	(1.82)	(38,382)	(36,410)
Leaf rust	0.27	0.17	0.86	0.76	83,176**	71,540**
	(0.34)	(0.32)	(2.04)	(2.00)	(33,097)	(32,401)
Stripe rust	-0.31	0.06	-1.77***	-1.33**	-45,928***	-29,414*
	(0.29)	(0.28)	(0.58)	(0.57)	(16,753)	(17,428)
Loose smut	-1.03***	-0.69***	-2.31***	-2.25***	-90,287***	-85,233***
	(0.28)	(0.26)	(0.47)	(0.46)	(29,334)	(27,483)
Bunt	-0.53**	-0.34	1.16*	1.15*	61,183	59,974
	(0.25)	(0.23)	(0.60)	(0.59)	(50,317)	(51,085)
Leaf spot	1.46***	1.27***	0.88	0.57	27,316	19,912
	(0.46)	(0.43)	(0.89)	(0.88)	(41,856)	(38,542)
Fusarium head blight	0.07	-0.39	-6.16***	-6.19***	-59,049	-55,740
	(0.33)	(0.32)	(2.25)	(2.07)	(55,866)	(56,354)
Sprouting	-0.53	-0.42	1.01	0.72	-16,964	-21,746
	(0.35)	(0.33)	(1.05)	(1.02)	(37,212)	(39,531)
Lodging	0.63	0.22	1.95***	1.83***	93,441**	85,738**
	(0.43)	(0.40)	(0.50)	(0.49)	(44,217)	(40,481)
Height	-0.41	-0.35	-0.57	-0.65	-33,858	-37,478

	(0.72)	(0.67)	(0.78)	(0.77)	(32,162)	(31,396)
Head awn	-1.14	-0.33	37.30	36.22		
	(0.88)	(0.82)	(547.74)	(1,309.89)		
Maturity rate	-1.41***	-1.06***	-0.01	0.13	-23,268	-26,650
	(0.34)	(0.31)	(0.24)	(0.23)	(21,179)	(21,118)
Test weight	-0.29	-0.18	0.02	-0.00	-4,678	-8,490
	(0.25)	(0.23)	(0.25)	(0.25)	(13,506)	(13,172)
Seed weight	0.05	-0.01	-0.16	-0.23	14,663	13,695
	(0.20)	(0.18)	(0.27)	(0.26)	(14,929)	(14,545)
Wheat class dummy variables	✓	✓				
var(*share*)	14.93***	12.82***	3.75***	3.61***		
	(1.40)	(1.19)	(0.35)	(0.33)		
Constant	0.78	3.65	81.17	76.85	4,966,694**	4,957,456***
	(11.38)	(10.73)	(548.36)	(1,310.14)	(2,052,023)	(1,801,957)
Observations	310	310	310	310	310	310
R^2					0.41	0.42

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.5: Hard red spring estimates using alternative econometric approaches

Variables	(D25) Tobit	(D26) Tobit	(D27) Fixed effects Tobit	(D28) Fixed effects Tobit	(D29) Two-way fixed effects	(D30) Two-way fixed effects
Dependent variables:	Share				acres	
Lag yield potential		0.11**		0.12***		6,120***
		(0.05)		(0.04)		(1,822)
Lag average yield	-0.06		0.00		1,579	
	(0.05)		(0.05)		(2,066)	
Lag variety specificity		-2.85***		-2.23***		-51,242***
		(0.30)		(0.29)		(12,526)
Lag yield variance	-0.01		-0.01		5.09	
	(0.01)		(0.01)		(261.25)	
Age	0.09	-0.05	0.22***	0.06	10,832	4,845
	(0.07)	(0.06)	(0.07)	(0.07)	(8,159)	(6,811)
Age^2	-0.00	0.00	-0.00***	-0.00*	-68.58**	-40.34
	(0.00)	(0.00)	(0.00)	(0.00)	(31.15)	(27.24)
Age^3	0.00	-0.00	0.00***	0.00*	0.14**	0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.06)
Protein	-1.51	-1.05	-4.54**	-1.92	-127,170	-69,853
	(1.31)	(1.20)	(2.02)	(1.89)	(118,742)	(102,395)
Stripe rust	0.91**	1.02***	-2.47***	-1.27	-70,308*	-41,196
	(0.40)	(0.37)	(0.86)	(0.81)	(39,217)	(34,328)
Loose smut	-0.36	-0.03	-0.43	1.71	31,803	85,491
	(0.39)	(0.36)	(5.34)	(5.20)	(68,237)	(56,035)
Bunt	-1.29***	-1.13***	0.06	-0.12	1,116	-6,160
	(0.33)	(0.30)	(1.01)	(0.94)	(51,300)	(37,479)
Leaf spot	0.55	0.23	-2.88	-3.70*	-129,203	-134,114*
	(0.61)	(0.56)	(2.07)	(1.95)	(105,132)	(70,471)
Fusarium head blight	0.50	-0.19	-10.42***	-9.09***	-186,778***	-137,134***
	(0.46)	(0.43)	(3.52)	(3.27)	(45,054)	(48,651)
Sprouting	-0.06	-0.03	2.13	1.94	26,831	34,162
	(0.39)	(0.35)	(1.96)	(1.82)	(103,428)	(81,890)
Lodging	0.89	0.37	0.80	-0.13	32,146	-4,474
	(0.66)	(0.62)	(1.26)	(1.20)	(38,082)	(24,413)
Height	-4.10***	-2.94***	-4.14***	-2.23**	-141,573***	-89,453***
	(0.84)	(0.77)	(1.03)	(0.99)	(43,454)	(32,947)
Head awn	-0.24	0.84	-2.11	-0.13		
	(1.14)	(1.04)	(3.37)	(3.16)		
Maturity rate	-1.17**	-1.00**	-0.84	-0.42	-13,019	-7,990

	(0.54)	(0.49)	(0.65)	(0.61)	(19,995)	(23,637)
Provincial dummy variables	✓	✓	✓	✓	✓	✓
var(*share*)	44.06***	35.89***	28.80***	24.70***		
	(3.58)	(2.88)	(2.32)	(1.98)		
Constant	35.40*	29.57	124.95***	69.56*	2,771,787*	1,489,239
	(20.88)	(18.92)	(43.60)	(41.68)	(1,552,840)	(1,396,786)
Observations	378	378	378	378	380	380
R^2					0.53	0.60

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table D.6: Canada Prairie spring estimates using alternative econometric approaches

	(D31)	(D32)	(D33)	(D34)	(D35)	(D36)
Variables	Tobit	Tobit	Fixed effects Tobit****	Fixed effects Tobit	Two-way fixed effects	Two-way fixed effects
Dependent variable:			share		acres	
Lag yield potential		0.06*		0.01		1,583
		(0.03)		(0.02)		(1,715)
Lag average yield	-0.00		-0.00		-9.31	
	(0.04)		(0.02)		(1,152)	
Lag variety specificity		-0.34***		-0.16**		-12,377***
		(0.12)		(0.08)		(2,516)
Lag yield variance	-0.00		-0.00		-48.58	
	(0.00)		(0.00)		(82.30)	
Age	-0.02	-0.03	-0.11**	-0.13**	27.22	-7,257
	(0.08)	(0.07)	(0.05)	(0.05)	(10,210)	(7,456)
Age^2	0.00	0.00	0.00**	0.00**	21.60	27.74
	(0.00)	(0.00)	(0.00)	(0.00)	(30.90)	(20.76)
Age^3	-0.00	-0.00	-0.00**	-0.00***	-0.08	-0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.05)
Protein	-2.06**	-2.16***	-2.32**	-2.24**	-42,024	-52,934**
	(0.79)	(0.74)	(0.67)	(0.68)	(24,407)	(19,723)
Stripe rust	-0.19	-0.18	0.68	-0.22	-21,901	-41,845**
	(0.49)	(0.45)	(1.07)	(1.11)	(34,483)	(18,314)
Loose smut	1.26*	1.07	-4.40	-3.47	46,628	-94,980
	(0.69)	(0.68)	(226.40)	(223.66)	(174,927)	(132,587)
Bunt	0.69	0.89*	4.68	3.85	19,860	144,501
	(0.50)	(0.46)	(226.40)	(223.66)	(159,320)	(120,580)
Leaf spot	1.40	0.89	2.91***	2.33***		
	(1.21)	(1.14)	(0.79)	(0.83)		
Fusarium head blight	1.24*	0.96*	-10.77	-10.52	28,164	-167,155
	(0.57)	(0.54)	(1,132)	(1,118)	(219,939)	(178,910)
Sprouting	-0.42	-0.98	-0.52	-0.72	-131,343	-120,785
	(0.97)	(0.94)	(0.98)	(0.99)	(110,390)	(80,437)
Lodging	-0.38	-0.29	-0.60	-0.81	-41,874	-11,142
	(1.03)	(0.98)	(0.78)	(0.77)	(54,657)	(33,402)
Height	1.49*	1.15	1.62**	1.48***	19,118	3,437
	(0.81)	(0.77)	(0.50)	(0.49)	(23,351)	(15,562)
Head awn	-2.36	-3.13	-21.37	-21.09		
	(2.10)	(1.97)	(2,038)	(2,013)		

Maturity rate	0.26	0.55	0.61	0.63*	1,312	6,259
	(0.52)	(0.50)	(0.37)	(0.36)	(20,463)	(16,948)
Provincial dummy variables	✓	✓	✓	✓	✓	✓
var(*share*)	3.12***	2.70***	0.78***	0.73***		
	(0.67)	(0.58)	(0.16)	(0.15)		
Constant	15.42	18.52	57.40	61.79	799,037	1,585,581**
	(12.80)	(12.21)	(3,622)	(3,579)	(1,119,656)	(663,469)
Observations	67	67	67	67	67	67
R^2					0.85	0.89

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**** For Model (D33) convergence is not achieved.

Table D.7: Durum estimates using alternative econometric approaches

Variables	(D37) Tobit	(D38) Tobit	(D39) Fixed effects Tobit	(D40) Fixed effects Tobit	(D41) Two-way fixed effects	(D42) Two-way fixed effects
Dependent variable:			share		acres	
Lag yield potential		0.18***		0.01		3,414
		(0.06)		(0.03)		(3,103)
Lag average yield	0.21**		0.01		2,902	
	(0.08)		(0.04)		(4,612)	
Lag variety specificity		-1.36***		-0.38*		-8,606
		(0.37)		(0.21)		(10,242)
Lag yield variance	-0.01		-0.01		144.47	
	(0.01)		(0.01)		(366.49)	
Age	0.38***	0.35***	0.33***	0.33***	11,966	8,986
	(0.07)	(0.06)	(0.06)	(0.06)	(9,407)	(8,722)
Age^2	-0.00***	-0.00***	-0.00***	-0.00***	-130.56***	-129.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(39.18)	(35.01)
Age^3	0.00***	0.00***	0.00***	0.00***	0.19***	0.19***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.05)
Protein	5.05**	2.78	-2.30	-3.55	-428,597	-490,939
	(2.36)	(2.23)	(5.38)	(5.24)	(308,330)	(301,400)
Stripe rust	-4.34**	-1.60	1.13	0.93	-113,259*	-132,480*
	(1.79)	(1.80)	(2.16)	(2.14)	(58,423)	(65,723)
Loose smut	-0.79	-0.74	-1.54***	-1.50***	-43,336	-40,911
	(0.83)	(0.76)	(0.46)	(0.45)	(27,886)	(25,027)
Bunt	6.89***	6.05***	7.57***	7.51***	179,796**	192,446**
	(1.58)	(1.48)	(1.62)	(1.58)	(72,179)	(66,605)
Leaf spot	-4.08**	-2.83*	5.34***	5.26***	234,490*	238,479*
	(1.56)	(1.43)	(1.42)	(1.39)	(117,733)	(114,386)
Fusarium head blight	-6.80***	-8.41***	-6.57	-5.66		
	(2.27)	(2.11)	(5.24)	(5.17)		
Sprouting	4.39***	2.79*	-2.91	-2.64	-39,501	-7,183
	(1.42)	(1.40)	(2.75)	(2.72)	(64,101)	(62,190)
Lodging	-0.25	-0.61	2.33**	2.34**	145,101	146,861
	(0.94)	(0.87)	(0.97)	(0.92)	(128,785)	(131,674)
Height	18.67***	17.55***	7.33	7.56		
	(4.06)	(3.65)	(6.91)	(6.74)		
Head awn	-	-	-	-		
Maturity rate	-3.55***	-2.56***	-2.25***	-2.05***	-114,885***	-101,596**

	(1.06)	(0.96)	(0.61)	(0.57)	(37,614)	(34,207)
Provincial dummy variables	✓	✓	✓	✓	✓	✓
var(*share*)	12.02***	10.46***	2.46***	2.40***		
	(2.21)	(1.91)	(0.45)	(0.44)		
Constant	-141.35***	-106.87***	-29.64	-12.31	4,234,517	4,941,162
	(31.47)	(30.42)	(84.34)	(81.89)	(3,743,304)	(3,648,341)
Observations	74	74	74	74	81	81
R^2					0.92	0.92

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.8: Prairie-wide estimates for full dataset

Variables	(D43) Pooled OLS	(D44) Pooled OLS	(D45) Hausman-Taylor IV	(D46) Hausman-Taylor IV	(D47) FEF Step (1)	(D47) FEF Step (2)	(D48) FEF Step (1)	(D48) FEF Step (2)
	Dependent variable: acres							
Lag yield potential		3,764***		-65.37			2,267***	
		(866.93)		(509.20)			(594.73)	
Lag average yield	1,527		-881.81*		626.36			
	(1,188)		(532.58)		(641.20)			
Lag variety specificity		-22,459***		-3,486			-13,464***	
		(5,257)		(2,739)			(4,741)	
Lag yield variance	-53.27		44.57		44.51			
	(66.10)		(31.83)		(60.08)			
Age	2,544**	1,772*	3,887**	3,744**	2,901*		2,333	
	(1,196)	(1,012)	(1,758)	(1,707)	(1,607)		(1,554)	
Age^2	-15.84**	-10.69*	-32.89***	-31.20***	-28.09***		-22.60**	
	(6.88)	(5.68)	(11.14)	(10.88)	(10.25)		(9.98)	
Age^3	0.03**	0.02*	0.05***	0.05***	0.05**		0.04**	
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)		(0.02)	
Protein	21,621	15,661	16,606	18,340	-120,499**		-110,194**	
	(23,706)	(21,791)	(89,099)	(86,889)	(57,812)		(52,104)	
Stripe rust	9,384	9,326	6,750	7,627	-60,853		-50,836	
	(9,600)	(8,347)	(13,331)	(13,209)	(37,279)		(33,336)	
Loose smut	-3,315	-3,166	-42,614**	-40,941*	-23,835		-19,389	
	(13,007)	(11,987)	(21,502)	(21,460)	(38,453)		(36,273)	
Bunt	-17,898	-13,683	20,368	18,625	47,163		41,154	
	(15,816)	(14,153)	(27,896)	(27,910)	(43,453)		(42,159)	
Leaf spot	36,016	32,650	-2,775	-1,313	22,819		21,785	
	(26,093)	(23,733)	(35,103)	(34,751)	(55,596)		(51,698)	
Fusarium head blight	5,075	-1,901	-11,043	-11,512	-9,522		-13,124	
	(17,042)	(15,340)	(17,570)	(17,682)	(31,607)		(31,946)	
Sprouting	1,670	-4,450	-2,222	-3,814	-50,894		-34,347	
	(14,557)	(13,662)	(19,749)	(19,027)	(63,341)		(57,743)	
Lodging	23,139*	4,809	59,016**	56,806*	22,826		22,643	
	(14,271)	(14,347)	(29,259)	(29,092)	(23,554)		(22,352)	
Height	-57,629**	-55,784**	-49,405**	-50,463**	-53,490*		-54,605**	
	(28,563)	(26,431)	(20,542)	(20,749)	(27,853)		(25,375)	
Head awn	19,976	22,764	-46,587	-37,877		-180,808***		-139,871***
	(39,034)	(34,030)	(80,232)	(81,193)		(57,996)		(49,551)

Maturity rate	-9,720	-5,950	10,209	12,429*	-1,311		3,661	
	(9,016)	(8,164)	(7,072)	(7,327)	(13,343)		(12,970)	
Provincial dummy variables	✓	✓	✓	✓	✓	✓	✓	✓
Wheat class dummy variables	✓	✓						
Constant	-344,697	-221,820	-193,142	-240,379	2,090,138**	115,801**	1,807,750**	88,811**
	(442,009)	(397,332)	(1,355,023)	(1,318,551)	(941,268)	(46,884)	(856,611)	(38,898)
Observations	661	661	661	661	692	661	692	661
R^2	0.15	0.25			0.52	0.13	0.55	0.11
Number of varieties	81	81	81	81	83	81	83	81

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.9: Alberta provincial estimates for full dataset

Variables	(D49) Pooled OLS	(D50) Pooled OLS	(D51) Hausman-Taylor IV	(D52) Hausman-Taylor IV	(D53) FEF		(D54) FEF	
					Step (1)	Step (2)	Step (1)	Step (2)
	Dependent variable: acres							
Lag yield potential		3,786***		186.14			-274.37	
		(1,341)		(719.98)			(711.84)	
Lag average yield	1,312		479.17		-37.31			
	(1,466)		(652.96)		(661.03)			
Lag variety specificity		-20,262***		1,211			-298.53	
		(5,151)		(1,862)			(1,596)	
Lag yield variance	-161.17		157.48***		56.92			
	(121.79)		(60.15)		(47.33)			
Age	7,701*	8,942**	9,145***	8,538***	8,347**		7,987**	
	(4,050)	(3,996)	(3,288)	(3,245)	(3,227)		(3,228)	
Age^2	-49.45	-58.50*	-72.65***	-65.26***	-65.50**		-61.37**	
	(31.12)	(30.20)	(26.06)	(25.12)	(25.99)		(25.71)	
Age^3	0.10	0.11*	0.15**	0.13**	0.12**		0.11**	
	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)		(0.05)	
Protein	-66,362	-49,712	50,898	35,204	92,105		92,141	
	(67,749)	(56,453)	(43,208)	(38,848)	(59,870)		(59,319)	
Stripe rust	43,538*	40,166*	30,930***	30,704***	27,785***		28,961***	
	(25,152)	(23,051)	(10,998)	(10,612)	(7,885)		(8,101)	
Loose smut	71,964	60,551	47,378	50,268*		76,533		78,731
	(42,948)	(39,311)	(29,422)	(29,143)		(49,794)		(49,998)
Bunt	-11,542	-6,068	-20,029	-29,894	-244,683***		-249,035***	
	(24,997)	(20,764)	(22,248)	(23,179)	(35,449)		(35,198)	
Leaf spot	-63,594	-59,688	-143,287***	-135,734***	-		-	
	(83,921)	(78,813)	(48,242)	(49,075)				
Fusarium head blight	-16,311	-1,374	-44,616	-47,154		-122,522		-119,092
	(32,463)	(29,047)	(41,545)	(42,523)		(86,470)		(86,476)
Sprouting****	29,214	22,562	19,390	23,170	81,990***		81,099***	
	(28,891)	(24,264)	(26,764)	(25,545)	(25,211)		(25,605)	
Lodging	-35,662	-58,307	19,432	16,929	31,200		12,330	
	(88,818)	(79,165)	(43,061)	(40,040)	(26,022)		(23,102)	
Height	-118,256	-99,009	-127,684	-116,574		84,692		83,516
	(93,405)	(78,698)	(87,094)	(84,998)		(146,438)		(142,927)
Head awn	76,945	44,228	31,636	50,067		473,579***		482,092***
	(82,774)	(68,829)	(71,370)	(70,079)		(158,240)		(156,259)

Maturity rate	78,889	64,772	91,607*	91,061**	106,028*		101,273**	
	(50,177)	(45,030)	(48,468)	(46,112)	(53,022)		(49,931)	
Test weight	15,103	15,550	3,793	7,420	-1,333		709.00	
	(32,107)	(28,074)	(15,028)	(14,710)	(12,695)		(11,650)	
Seed weight	11,254	9,180	4,643	13,514	16,757		19,245	
	(16,213)	(14,530)	(13,095)	(12,897)	(24,366)		(21,534)	
Wheat class dummy variables	✓	✓						
Constant	-772,959	-996,893	-1,166,698	-1,501,640	-1,888,814	-468,930	-1985268	-480,214
	(1,967,779)	(1,741,196)	(1,603,276)	(1,598,890)	(1,755,292)	(456,146)	(1,603,138)	(448,873)
Observations	143	143	143	143	178	143	178	143
R^2	0.43	0.51			0.92	0.24	0.91	0.25
Number of varieties	39	39	39	39	53	39	53	39

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**** sprouting is time variant in Alberta when no restriction on a minimum of risk areas is imposed

Table D.10: Manitoba provincial estimates for full dataset

Variables	(D55) Pooled OLS	(D56) Pooled OLS	(D57) Hausman-Taylor IV	(D58) Hausman-Taylor IV	(D59) FEF Step (1)	(D59) FEF Step (2)	(D60) FEF Step (1)	(D60) FEF Step (2)
	Dependent variable: acres							
Lag yield potential		-1,050		-1,354**			-691.47	
		(824.67)		(640.44)			(714.54)	
Lag average yield	-1,326*		-891.65		118.89			
	(731.38)		(607.50)		(1,445)			
Lag variety specificity		-3,448		620.58			-3,426	
		(7,278)		(2,837)			(7,022)	
Lag yield variance	-64.78		-181.46		-53.94			
	(165.40)		(110.85)		(198.87)			
Age	-1,429	-1,592	840.92	810.99	4,607		4,656	
	(2,384)	(2,314)	(1,099)	(1,071)	(3,397)		(3,232)	
Age^2	0.93	2.26	-28.26***	-27.95***	-58.90**		-58.42**	
	(16.86)	(17.25)	(8.14)	(7.86)	(24.13)		(22.24)	
Age^3	0.00	-0.00	0.07***	0.06***	0.13**		0.13**	
	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)		(0.05)	
Protein	74,304	75,724	121,429**	140,363**	339,660		332,098	
	(64,627)	(65,480)	(52,252)	(56,681)	(262,491)		(243,139)	
Stem rust	-142,998	-140,948*	-261,116***	-265,640***	-264,861***		-269,527***	
	(81,209)	(72,816)	(67,307)	(65,068)	(88,543)		(70,563)	
Leaf rust	32,069	31,473	67,036	69,578		61,690		71,257
	(52,053)	(63,310)	(146,685)	(149,888)		(114,471)		(109,758)
Stripe rust	-10,457	-11,741	-1,723	2,760	58,082		57,116	
	(29,382)	(29,928)	(17,683)	(16,686)	(47,538)		(42,466)	
Loose smut	-135,481***	-132,983***	43,423	36,054		46,259		40,606
	(16,573)	(23,170)	(61,166)	(62,774)		(37,785)		(36,985)
Bunt	50,437*	48,137*	-28,400	-22,496	-55,486		-51,406*	
	(26,164)	(23,906)	(24,636)	(24,008)	(36,616)		(30,271)	
Leaf spot	-386,561***	-377,233***	-273,557	-278,272		-60,808		-72,753
	(98,742)	(75,691)	(306,929)	(301,297)		(256,705)		(247,169)
Fusarium head blight	47,278	44,430	-142,169***	-135,498***	-201,667***		-195,487***	
	(51,355)	(66,494)	(48,033)	(47,713)	(43,927)		(41,960)	
Sprouting	-43,661*	-42,021**	89,100***	82,134**	72,505		75,994	
	(20,227)	(15,565)	(30,807)	(36,049)	(66,429)		(57,956)	
Lodging	23,364	24,440	-4,566	401.59		-12,136		-74.35
	(30,693)	(30,949)	(169,765)	(171,503)		(142,599)		(138,556)

Height	-49,332	-49,573	-35,199	-37,286	-36,008		-40,472	
	(30,853)	(29,147)	(25,548)	(26,294)	(31,952)		(31,208)	
Head awn	-697,191***	-679,131***	-87,553	-126,707		-59,329		-61,323
	(110,835)	(99,933)	(233,457)	(229,071)		(164,504)		(158,001)
Maturity rate	-510,347***	-499,875***	-358,405	-371,665		-182,211		-190,188
	(125,542)	(93,209)	(274,154)	(269,490)		(280,027)		(270,093)
Seed weight	-227,430***	-222,547**	-22,979	-26,169		92,700		98,093
	(70,560)	(79,727)	(295,704)	(294,268)		(236,140)		(226,727)
Wheat class dummy variables	✓	✓						
Constant	3,286,794**	3,199,731**	1,246,494	1,073,872	-147,141	147,141	-3,001,588	115,301
	(1,346,727)	(1,407,267)	(3,415,813)	(3,357,008)	(2,584,537)	(2,584,537)	(3,429,113)	(2,491,199)
Observations	88	88	88	88	147	88	147	88
R^2	0.73	0.73			0.78	0.23	0.78	0.24
Number of varieties	14	14	14	14	32	14	32	14

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.11: Saskatchewan provincial estimates for full dataset

Variables	(D61) Pooled OLS	(D62) Pooled OLS	(D63) Hausman-Taylor IV	(D64) Hausman-Taylor IV	(D65) FEF Step (1)	(D65) FEF Step (2)	(D66) FEF Step (1)	(D66) FEF Step (2)
	Dependent variable: acres							
Lag yield potential		2,794**		-103.95			-337.09	
		(1,231)		(774.28)			(770.24)	
Lag average yield	271.06		-1,643**		-1,851**			
	(1,155)		(799.75)		(821.05)			
Lag variety specificity		-13,908***		-1,423			-296.68	
		(4,610)		(3,521)			(3,443.58)	
Lag yield variance	4.88		74.49		82.85			
	(47.13)		(50.21)		(50.87)			
Age	4,378**	3,614**	4,903***	4,884***	4,837***		4,929***	
	(1,717)	(1,447)	(1,616)	(1,606)	(1,660)		(1,639)	
Age^2	-27.98***	-22.67**	-36.83***	-36.09***	-37.78***		-37.79***	
	(10.32)	(8.61)	(9.94)	(10.26)	(9.54)		(9.79)	
Age^3	0.05***	0.04**	0.06***	0.06***	0.06***		0.06***	
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)		(0.02)	
Protein	16,185	12,195	-138,657	-126,574	-247,042		-233,772	
	(33,865)	(31,922)	(138,577)	(137,334)	(164,557)		(168,853)	
Stem rust	-7,358	-4,228	20,745	20,694	14,670		14,402	
	(16,258)	(14,354)	(26,433)	(24,260)	(33,970)		(31,291)	
Leaf rust	12,464	11,942	69,760**	67,483**	83,224***		83,297***	
	(15,574)	(14,920)	(33,305)	(32,732)	(27,112)		(25,405)	
Stripe rust	-3,211	-2,392	-36,635*	-33,722*	-43,254**		-40,663*	
	(17,174)	(15,857)	(19,391)	(19,527)	(20,900)		(21,365)	
Loose smut	-27,222**	-22,680**	-62,000***	-60,567***	-80,435***		-79,156***	
	(10,688)	(10,175)	(22,247)	(22,691)	(28,409)		(29,311)	
Bunt	-8,775	-5,326	66,874*	66,292*	68,875		68,766	
	(12,810)	(11,838)	(39,269)	(38,868)	(46,224)		(46,024)	
Leaf spot	61,542***	56,334***	16,434	16,718	26,742		26,719	
	(21,248)	(19,583)	(38,505)	(34,766)	(47,237)		(42,948)	
Fusarium head blight	12,198	3,317	-12,914	-11,802	-26,701		-24,991	
	(17,794)	(17,490)	(13,259)	(14,044)	(20,943)		(22,604)	
Sprouting	-3,157	-5,767	-19.78	-3,422	6,561		2,412	
	(15,535)	(14,835)	(27,011)	(26,287)	(39,521)		(38,121)	
Lodging	22,349*	6,933	82,030***	79,479***	92,089***		90,754***	
	(12,088)	(10,759)	(30,265)	(29,809)	(33,077)		(32,849)	

Height	-509.09	-8,580	-16,990	-19,595	-16,437		-18,863	
	(27,128)	(24,586)	(19,437)	(20,288)	(21,275)		(22,723)	
Head awn	-35,711	-30,818	-208,020*	-198,876*		-290,814***		-282,581***
	(37,840)	(34,055)	(114,529)	(114,093)		(81,668)		(80,015)
Maturity rate	-17,874*	-13,650	8,658	11,377	11,293		13,944	
	(9,713)	(8,965)	(8,340)	(8,905)	(8,875)		(9,456)	
Test weight	-6,386	-2,293	13,310	14,136	16,261		16,740	
	(8,863)	(8,494)	(11,348)	(11,611)	(11,876)		(12,201)	
Seed weight	8,965	8,104	4,877	3,896	11,731		11,170	
	(6,947)	(6,754)	(8,898)	(8,546)	(10,051)		(9,979)	
Wheat class dummy variables	✓	✓						
Constant	-374,836	-322,776	1,533,436	1,308,693	2,951,388	201,570***	2,701,421	195,863***
	(563,156)	(512,369)	(1,944,397)	(1,907,489)	(2,368,325)	(64,587)	(2,411,201)	(63,596)
Observations	378	378	378	378	378	378	378	378
R^2	0.25	0.29			0.76	0.17	0.75	0.17
Number of varieties	72	72	72	72	72	72	72	72

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table D.12: Hard red spring wheat class estimates for full dataset

Variables	(D67) Pooled OLS	(D68) Pooled OLS	(D69) Hausman-Taylor IV	(D70) Hausman-Taylor IV	(D71) FEF Step (1)	(D71) FEF Step (2)	(D72) FEF Step (1)	(D72) FEF Step (2)
Dependent variable: acres								
Lag yield potential		2,878***		-355,40			2,579***	
		(882.34)		(571.80)			(745.78)	
Lag average yield	276.15		-1,027		1,204			
	(1,284)		(694.00)		(778.13)			
Lag variety specificity		-30,318***		-3,538			-20,434***	
		(6,057)		(2,672)			(6,259)	
Lag yield variance	-109.88		87.75		35.82			
	(122.68)		(85.26)		(123.51)			
Age	3,114	1,438	8,000**	7,534**	4,551		2,645	
	(1,928)	(1,721)	(3,396)	(3,188)	(3,147)		(2,988)	
Age^2	-22.98	-10.96	-75.14***	-70.60***	-47.55*		-30.55	
	(13.76)	(12.37)	(25.15)	(23.53)	(26.41)		(25.42)	
Age^3	0.05	0.02	0.16***	0.15***	0.10*		0.07	
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)		(0.06)	
Protein	-25,916	-25,548	-9,343	-9,022	-114,325		-99,895	
	(36,985)	(35,350)	(140,752)	(136,749)	(97,277)		(89,527)	
Stripe rust	26,673**	23,560**	1,704	2,253	-75,127**		-54,390*	
	(10,378)	(8,842)	(11,011)	(11,489)	(36,482)		(31,262)	
Loose smut	-1,328	-1,707	15,942	14,734	36,377		52,286	
	(16,243)	(15,113)	(17,441)	(17,461)	(48,875)		(49,844)	
Bunt	-29,499	-23,942	-22,031	-22,450	-5,549		-9,276	
	(19,421)	(17,489)	(22,361)	(22,098)	(48,875)		(40,314)	
Leaf spot	13,940	13,152	-23,283	-20,366	-38,761		-37,598	
	(31,411)	(28,394)	(30,417)	(30,662)	(65,829)		(56,130)	
Fusarium head blight	17,286	6,643	-8,568	-8,536	593		5,136	
	(20,695)	(18,901)	(22,114)	(22,092)	(45,633)		(44,321)	
Sprouting	5,624	3,168	3,000	3,053	-24,300		950.15	
	(14,652)	(13,512)	(19,858)	(18,430)	(80,270)		(70,636)	
Lodging	7,952	-4,105	62,241*	63,996*	32,303		38,782	
	(20,812)	(19,813)	(37,401)	(38,589)	(33,392)		(30,010)	
Height	-94,068***	-90,388***	-76,804***	-77,724***	-83,155**		-82,142***	
	(29,608)	(26,272)	(26,545)	(26,495)	(32,944)		(29,261)	
Head awn	-11,354	4,377	-32,285	-22,306		-125,982**		-66,922

	(40,204)	(36,235)	(77,827)	(79,684)		(56,302)		(49,483)
Maturity rate	-5,700	-4,723	20,323**	22,522**	14,852		19,714	
	(9,886)	(9,360)	(9,574)	(10,048)	(12,548)		(11,861)	
Provincial dummy variables	✓	✓	✓	✓	✓		✓	
Constant	554,874	586,173	141,743	110,754	2,051,556	69,562	1,586,163	36,568
	(573,308)	(545,769)	(2,121,441)	(2,060,903)	(1,392,579)	(47,583)	(1,329,499)	(40,375)
Observations	467	467	467	467	480	467	480	467
R^2	0.19	0.30			0.50	0.11	0.54	0.05
Number of varieties	49	49	49	49	50	49	50	49

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table D.13: Canada Prairie spring wheat class estimates for full dataset

Variables	(D73) Pooled OLS	(D74) Pooled OLS	(D75) Hausman-Taylor IV	(D76) Hausman-Taylor IV	(D77) FEF Step (1)	(D77) FEF Step (2)	(D78) FEF Step (1)	(D78) FEF Step (2)
Lag yield potential		869.90		131.40			312.16	
		(595.88)		(310.55)			(619.75)	
Lag average yield	129.01		-305.69		-251.51			
	(803.11)		(404.15)		(843.27)			
Lag variety specificity		-4,824*		-606.46			-5,117*	
		(2,505)		(731.32)			(2,409)	
Lag yield variance	-32.41		14.27		-35.05			
	(36.84)		(11.02)		(23.96)			
Age	210.36	195.76	-2,701*	-2,539*	-3,935		-3,817	
	(2,658)	(2,637)	(1,408)	(1,361)	(2,722)		(2,519)	
Age^2	-4.95	-5.30	31.41**	30.58**	38.66		38.03	
	(24.39)	(23.93)	(15.65)	(15.31)	(23.28)		(22.17)	
Age^3	0.02	0.02	-0.11**	-0.10**	-0.12*		-0.12*	
	(0.06)	(0.06)	(0.04)	(0.04)	(0.06)		(0.06)	
Protein	-43,690*	-44,707*	12,428	15,526	-31,927		-32,876**	
	(23,259)	(23,604)	(21,491)	(24,210)	(19,021)		(13,621)	
Stripe rust	-512.28	-1,632	-6,718	-9,634	-8,368		196.45	
	(11,450)	(11,632)	(27,973)	(26,222)	(20,517)		(14,397)	
Loose smut	11,594	12,335	23,993	28,667	-		-	
	(15,874)	(15,970)	(21,167)	(21,560)				
Bunt	22,121	24,274	3600	641.84	52,564**		-39,591*	
	(20,325)	(18,854)	(16,638)	(16,085)	(22,995)		(22,278)	
Leaf spot	13,490	7,284	-10,300	-13,930		-38,065		-62,427
	(13,329)	(14,069)	(38,370)	(38,737)		(59,876)		(59,002)
Fusarium head blight	10,031	9,122	-21,883	-18,079	-55,257**		-46,457	
	(12,934)	(12,215)	(21,637)	(20,954)	(22,995)		(30,278)	
Sprouting	5,951	-2,241	26,018**	20,041**	-72,088		-80,049	
	(25,024)	(22,601)	(11,166)	(8,534)	(72,539)		(66,024)	
Lodging	20,130	16,379	1,988	-1,046	-16,542		-24,665*	
	(26,171)	(24,397)	(7,621)	(6,411)	(16,309)		(13,664)	
Height	33,685	31,122	8,840	10,359	44,031**		37,740**	
	(20,199)	(17,645)	(11,879)	(12,051)	(17,127)		(17,537)	
Head awn	-17,279	-33,391	10,185	3,747		-262,724***		-238,818***
	(47,876)	(44,050)	(48,910)	(51,901)		(46,798)		(43,198)
Maturity rate	11,340	15,332	-11,082*	-8,117	-5,412		-930.87	

	(15,497)	(15,089)	(6,098)	(6,608)	(11,317)		(11,025)	
Provincial dummy variables	✓	✓	✓	✓	✓		✓	
Constant	229,506	281,485	-100,503	-132,184	746,607*	336,350*	793,879**	384,018*
	(356,177)	(363,727)	(337,813)	(356,974)	(384,999)	(179,628)	(270,008)	(177,006)
Observations	88	88	88	88	93	88	93	88
R^2	0.45	0.48			0.79	0.30	0.81	0.29
Number of varieties	13	13	13	13	14	13	14	13

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.14: Durum wheat class estimates for full dataset

Variables	(D79) Pooled OLS	(D80) Pooled OLS	(D81) Hausman-Taylor IV	(D82) Hausman-Taylor IV	(D83) FEF		(D84) FEF	
					Step (1)	Step (2)	Step (1)	Step (2)
	Dependent variable: acres							
Lag yield potential		3,605*		-1,588			-897.59	
		(1,803)		(1,069)			(961.66)	
Lag average	4,536**		-2,604		-1,943			
	(2,062)		(1,619)		(1,253)			
Lag variety specificity		-25,565**		129.09			2,603	
		(9,038)		(6,934)			(5,517)	
Lag yield variance	-413.94		-29.43		79.63			
	(316.88)		(246.52)		(161.65)			
Age	12,524**	11,019**	10,092**	10,439**	7,476*		7,815*	
	(5,156)	(4,780)	(4,023)	(4,282)	(4,035)		(4,109)	
Age^2	-82.60**	-73.32**	-47.70***	-49.66***	-41.32**		-43.02**	
	(30.09)	(28.22)	(15.44)	(17.00)	(18.11)		(18.47)	
Age^3	0.13**	0.11**	0.06***	0.07***	0.06**		0.06**	
	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)		(0.02)	
Protein	321,156**	292,677**	345,494*	359,472	-31,146		-17,627	
	(135,031)	(128,858)	(213,483)	(218,915)	(86,627)		(80,152)	
Stripe rust	-215,880*	-169,727	66,303*	58,762*	-5,136		-9,863	
	(120,013)	(102,541)	(34,885)	(35,070)	(43,697)		(44,796)	
Loose smut	-39,383	-37,907	-66,683***	-64,559***	-93,149***		-91,510**	
	(38,056)	(33,378)	(17,107)	(17,238)	(30,892)		(32,007)	
Bunt	271,244***	254,309***	423,491***	422,877***	296,186***		294,890***	
	(63,992)	(64,287)	(23,609)	(24,065)	(51,961)		(51,055)	
Leaf spot	-117,551	-69,741	243,101***	233,781***	114,748		107,032	
	(89,460)	(77,864)	(89,406)	(86,583)	(118,722)		(119,702)	
Fusarium head blight	-82,753	-95,667	-17,207	-9,787		-184,776		-177,976
	(127,307)	(118,276)	(136,419)	(140,188)		(129,205)		(128,255)
Sprouting	132,441*	99,601	-118,242**	-118,920**	-11,657		-14,995	
	(71,917)	(63,586)	(58,371)	(60,005)	(56,191)		(52,621)	
Lodging	-12,747	-10,130	134,471*	129,805*	100,943		98,189	
	(40,635)	(40,398)	(72,381)	(69,139)	(67,269)		(66,001)	
Height	410,930**	311,182*	-7,682	-1,079		192,714***		198,517***
	(166,334)	(147,094)	(142,745)	(137,877)		(18,919)		(20,126)
Head awn	-	-				-		-

Maturity rate	-63,998	-40,691	-34,185*	-39,011*	-32,842		-36,849	
	(44,118)	(41,900)	(19,710)	(22,334)	(21,620)		(23,181)	
Provincial dummy variables	✓	✓	✓	✓	✓		✓	
Constant	-6,228,809**	-5,598,687**	-7,824,971**	-8,016,486**	-1,325,985	-313,734	-1,500,525	-341,723
	(2,243,834)	(2,162,401)	(3,135,183)	(3,259,023)	(1,140,783)	(239,696)	(1,062,143)	(238,680)
Observations	88	88	88	88	104	88	104	88
R^2	0.59	0.61			0.87	0.27	0.87	0.27
Number of varieties	17	17	17	17	17	17	17	17

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix E

Table E.1: Poolability F-test results when variety specificity is one of the key independent variables and a minimum of four risk areas of data is imposed

Analysis level	F-statistic	Prob>F
Prairies	4.17	0.00
Alberta	11.90	0.00
Manitoba	4.63	0.00
Saskatchewan	6.04	0.00
Hard red spring	4.11	0.00
Canada Prairie spring	8.84	0.00
Durum	10.84	0.00
H_o: variety specific effects equal		

Table E.2: Testing results for heteroskedasticity when variety specificity is one of the key independent variables and a minimum of four risk areas of data is imposed

Analysis level	Breusch-Pagan/ Cook-Weisberg test for heteroskedasticity		Modified Wald test for groupwise heteroskedasticity	
	χ^2- statistic	Prob>χ^2	χ^2- statistic	Prob>χ^2
Prairies	664.52	0.00		
Alberta			3.1e+31	0.00
Manitoba			60767.17	0.00
Saskatchewan			1.5e+05	0.00
Hard red spring	392.11	0.00		
Canada Prairie spring	10.92	0.010		
Durum	56.40	0.00		
H_o: variances equal				

Due to the nature of the dataset, I estimate adoption at the Prairie-wide and wheat class levels using the *regression* command and a factorial variety identifier in Stata. This allows for each province reporting on the same variety within a year. Alternatively, at the provincial level of analysis, this approach is not necessary and I use the *xtreg* command in Stata to estimate the models. As a result, I use the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity at the

Prairie-wide and wheat classes analysis levels, and the modified Wald test for groupwise heteroskedasticity at the provincial levels. In each case, the null hypothesis of homoskedasticity is rejected when the significance level is set at 5%. Given this presence of heteroskedasticity, and the differential nature of wheat varieties, I correct the standard errors by clustering on variety in the empirical results presented in chapter six.