Managing Risk in Agriculture:
A Spatial Bio-Economic Perspective

A DISSERTATION
SUBMITTED TO THE FACULTY OF
UNIVERSITY OF MINNESOTA
BY

YUAN CHAI

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Adviser: Philip G. Pardey
Co-Adviser: Terry M. Hurley

August 2018

Acknowledgements

First and foremost, I would like to express my sincere gratitude to my adviser, Dr. Phil Pardey, for his outstanding mentorship and invaluable support. Phil's belief and guidance ensured my smooth transition from a plant pathologist to an agricultural economist. When facing complex research problems, he always prompts me to "think as an economist" to find a creative solution. Discussions with Phil often produce fruitful outcomes and spark new research ideas. His contagious enthusiasm and strong work ethic inspire me daily to be a better researcher. His reviewing and editing profoundly improved the writing of this dissertation. Without him, this dissertation would not have been possible.

My co-adviser, Dr. Terry Hurley, also contributed substantially to my dissertation. Terry helped strengthen the technical details of my work and offered many insightful comments. It is truly a privilege to work with such an intelligent and amiable mentor. Dr. Brian Steffenson served as both my M.S. degree adviser and my Ph.D. committee member. His expertise in cereal crop production brought in valuable knowledge for linking my research to farmers and policy makers. The committee chair, Dr. Stephen Polasky, instilled in me a strong desire for interdisciplinary research and provided constructive criticism for my dissertation. Special thanks go to the late Dr. Jason Beddow, whose immense wisdom and vast knowledge helped in the origination and development of this dissertation. As an extension of his research work, this dissertation carries on his scholarly legacy.

In addition, I would like to thank all my colleagues at InSTePP, especially Connie Chan-Kang and Kevin Silverstein for their tireless efforts in collecting and cleaning data for this dissertation, and Michelle Hallaway for her thoughtful support throughout my work. I also thank my fellow classmates and friends for their unwavering support and friendship, which made my Ph.D. study years much more gratifying and memorable.

I am thankful for the financial support I received from the InSTePP center, the Hueg-Harrison Fellowship, and the Doctoral Dissertation Fellowship.

Last but not the least, I would like to thank my family for their love, encouragement and support. This accomplishment would not have been possible without them.

Dedication

In loving memory of my mother

Abstract

Agricultural production is an intrinsically risky business that involves many sources of risk, including production, market, institutional, and personal risks. The ever-changing bio-physical environments under which farmers operate result in highly uncertain production outcomes that vary markedly across space and over time. To cope with these multitude of risks, farmers' risk management strategies also vary over space and time. In this dissertation, I use U.S. wheat production to exemplify some novel, risk-centric assessments of the adoption of new crop varieties and the purchase of crop insurance as alternative, somewhat complementary risk management strategies.

First, I characterize the spatial and temporal dynamics of wheat varieties grown by U.S. farmers over the past century. Based on state-level area-by-variety data, and contrary to commonly held belief, I show that the landscape of wheat varieties grown in the United States became increasingly diverse both across space and over time during the study period 1919-2016. I then analyzed the effects of various risks on the spatio-temporal pattern of adoption of new wheat varieties, and find that past losses attributable to biotic risks are significantly correlated with the adoption of new varieties. Intuitively, farmers who experienced losses from crop pests and diseases are more likely than those not subject to pest losses to adopt new varieties with improved disease resistance. Lastly, I ask and answer the question "do biotic and abiotic risks have different consequences on the demand for crop insurance?" Using spatially disaggregated wheat production and insurance data in the United States for the period 1989-2016, my empirical results reinforce the implications of my theoretical model that farmers facing biotic risks are more likely to select lower amounts of crop insurance coverage compared with farmers facing abiotic risks.

Depending on the spatio-temporal dynamics of different types of risks, farmers draw on a number of technical, management, or market options to mitigate the negative consequences of these risks. Studying these agricultural risk management options from a bio-spatially sensitive perspective reveals new insights that can help policy makers and farmers implement better risk management strategies.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Since the inception of agriculture around 11,500 years ago, farmers have been dealing with the vagaries of weather, pests and diseases. These factors make agriculture an intrinsically risky business where production outcomes are not predictable with any certainty at the beginning of each growing season. Harwood et al. (1999) identified five major types of agricultural risks based on their sources: (1) production or yield risks caused by unfavorable weather events and pests and diseases; (2) price or market risks resulting from changes in the price of inputs or outputs from domestic or international markets; (3) institutional risks such as changes in policies and regulations regarding the production, processing, or sale of agricultural products; (4) human or personal risks caused by poor health or disruptive life events involving the principle agents on the farm; and (5) financial risks associated with the fluctuations in financial markets. The portfolio of risks that potentially affect an agricultural operation and their impacts on farmers' economic returns can be assessed through three main variables: hazard type (i.e., types of risk), vulnerability (i.e., potential impact of the realized risk), and exposure (i.e., specific farming operations that are subject to risk) (World Bank 2011). For crop production, the hazards faced by a farmer include a multitude of risks such as extreme weather events, crop diseases, and variability in input prices. For each of these risks, their frequency, severity and spatial extent can vary markedly. Moreover, the impact of these risks can range from inconsequential to extremely devastating depending on the operation's vulnerability to each of the different risks and the exposure faced by each farm.

To help farmers cope with various agricultural risks, it is important to understand in some detail the characteristics of the different types of risks and their spatio-temporal dynamics. For instance, the production risks faced by each farm may vary greatly depending on its geographic location given the intrinsic site-specific attributes of the biological and environmental processes involved. There are also distinctive characteristics between risks attributable to biotic versus abiotic stresses. Biotic risks arise from biological processes involving diseases, pests and weeds, while abiotic risks arise from physical processes related to weather, soil, terrain, or nutrient deficiency. The biological nature of agriculture and the interactions between biology and these various stress factors means that both the timing and location of production have important consequences for the risk profiles faced by farmers. Moreover, at any particular location and time, the risk exposure arising from biotic stresses may not be the same as those stemming from abiotic stresses. As a result, it is important for farmers to take into consideration these time and location specific attributes, as well as the particularities of each risk factor for optimal risk mitigation.

Given the multiple sources of risks and their various crop production and economic consequences, managing agricultural risk is an exceedingly challenging task. Farmers have different risk management strategies and tools they can use to cope with different types of agricultural risks. Depending on the timing of deployment, farmers' risk management behavior can be either anticipatory (i.e., *ex ante*) or responsive (i.e., *ex post*). *Ex ante* risk management actions take place before the occurrence of potential harmful events with the goal to avoid, prevent or mitigate adverse impacts. Examples of *ex ante* strategies include implementation of irrigation infrastructure for drought relief, adoption of disease resistant varieties and application of pesticides for disease prevention, hedging against price risks using futures and contracts, and the purchase of crop insurance to stabilize revenue. In contrast, *ex post* risk management strategies take place after the occurrence of adverse events, such as the provision of government aid and market loans after natural disasters, sale of farm assets and reallocation of farm labor to cope with financial hardship. Farmer's decision on which risk management strategies to choose and when to deploy them can be a very complex process depending on a number of factors, including the types of risks faced by each farmer, the management options available to them, past experience, operation capacity, financial resources, and personal preferences.

For crop farmers, one important *ex ante* risk management strategy is the choice of which particular crop variety to plant. Adoption of new varieties with advanced traits such as disease resistance or drought tolerance can help reduce production risk under biotic and abiotic stresses. In fact, with the advent of the Green Revolution in the 1960s, the adoption of modern high-yielding varieties for major food crops increased rapidly. Historically, a major risk factor faced by wheat farmers is the rust disease complex, comprised of stem, stripe and leaf rust caused by a group of fungal pathogens of the *Puccinia* species (McIntosh et al. 1995). The adoption of rust resistant varieties has successfully protected wheat farmers against the once devastating stem rust disease for several decades since the 1950s (Peterson 2001; Singh et al. 2006; Kolmer et al. 2007; Stokstad 2007). As an effective risk management tool, rust resistant wheat varieties have generated significant economic benefits globally, with an estimated value of $1.12 billion per year (2010 prices) for stem rust alone (Pardey et al. 2013), and potentially over $5 billion per year (2010 prices) for all three wheat rust diseases combined (Chai et al. 2018). However, new wheat varieties are constantly required to keep up with the ever-changing disease pressure associated with the persistent (co-)evolutionary genetic changes to pathogen populations.

The recent geographical spread of the stem rust Ug99 lineage across Africa, the Middle East and West Asia has raised concerns about the consequences of a lack of effective crop resistance to this new, virulent stem rust lineage (Singh et al. 2011). In the United States, public research and development (R&D) activities play a central role in providing wheat farmers with improved varieties that address various biotic and abiotic risks since private sector varietal improvement research for wheat is still limited (Fernandez-Cornejo 2004; Lesser and Kolady 2011; Brandl and Paula 2014).

Despite its yield enhancing benefits, the development of modern monoculture cropping systems is commonly believed to have reduced agricultural biodiversity, and increased the vulnerability of the cropped landscape to various production risks such as pests and diseases (Wilby and Thomas 2002; Gurr et al. 2003; Zhang et al. 2007; Cardinale et al. 2011). Thus, studying farmers' crop variety adoption history and the underlying driving forces for varietal adoption are consequential for understanding the exposure and risk avoidance strategies involved in modern agriculture. Unlike natural ecosystems, modern agriculture is a highly dynamic process given farmers' choice of crop varieties that vary across locations and over time. Spatially, breeders and farmers seek to grow varieties better adapted to local production realties. Over time, old crop varieties are abandoned as new varieties are released with advanced traits and higher yield potential and, often, performance. Modern agricultural systems change much faster over time compared with natural systems due to the constant development and uptake of new varieties. Thus, increasing both the spatial and temporal diversity of crop varieties is critical for maintaining the productivity of modern agricultural systems given ever-changing bio-physical environments.

In addition to the provision of improved crop varieties through public funded R&D activities, the U.S. federal government also provides a complex of farm programs aimed at providing a "safety net" for U.S. farmers, including direct payments, market loans, crop insurance and various payment programs (Coble and Barnett 2013; Pardey and Smith 2017). In fact, the first farm bill, the Agricultural Adjustment Act of 1933, was enacted in response to precipitous commodity price declines during the Great Depression and severe declines in crop yields caused by the Dust Bowl (Pardey and Smith 2017).

Among the various farm programs, the crop insurance program provided by the Federal Crop Insurance Corporation (FCIC) has gained great popularity with crop farmers and become their primary disaster protection program (Glauber 2013; Smith et al. 2017). Crop insurance can be classified into two major types; yield-based and revenue-based insurance products. Yield-based insurance contracts pay an indemnity when a farmer's actual yield falls below the insured yield level; revenue-based insurance contracts take into account both yield and price and provide a guarantee for a farmer's total revenue. Participation in revenue-based insurance has exceeded those in yield-based insurance in acres enrolled since 2003 (Glauber 2013).

However, the U.S. crop insurance program is far from socially and economically optimal given the large subsidies it receives through federal funds. Serious concerns have been raised regarding the economic waste associated with the current $7.0 billion spending on this crop insurance program, where, for instance, a substantial amount of the program's budget ($2.5 billion) flows directly to private crop insurance companies and agents each year (Pardey and Smith 2017; Smith et al. 2017). From the perspective of risk management, crop insurance provides protection for farmers through cash compensation after they experience losses, which is essentially a redistribution of dollars from taxpayers to farmers to help stabilize farmers' income. Even though crop insurance serves as an *ex ante* risk management strategy for farmers because their purchasing decisions occur before the actual production process, the protection provided by crop insurance is *ex post* in nature given that the indemnities are received by farmers only after the occurrence of losses. The intrinsic risks faced by agricultural producers (associated with various biotic and abiotic stresses) and the frequency, severity and spatial extent of these production risks are not reduced, and may be even increased, by the provision of crop insurance. In fact, the subsidized U.S. crop insurance program has been shown to encourage more risky production practices and expand production on to riskier land (Smith and Goodwin 1996; Goodwin et al. 2004; Goodwin and Smith 2013). Numerous improvements and reforms have been proposed to make the federal crop insurance program more socially and economically viable (Smith et al. 2017).

For agricultural policy makers, understanding the full social costs and benefits associated with different risk management options is important for the allocation of scarce public funds to help protect farmers against agricultural risks. In fiscal year 2017, the U.S. federal government spent a total of $22.7 billion on USDA programs that directly focus on farm and farming operations, of which 30.7 percent was spent on crop insurance subsidies, 38.0 percent on direct farm subsidy programs (Agricultural Risk Coverage and Price Loss Coverage), 20.8 percent on conservation, and only 10.4 percent on agricultural R&D (Pardey and Smith 2017). As exemplified by the history of developing and deploying rust resistant wheat varieties, spending on R&D activities for plant breeding and better management practices can help increase productivity and reduce farmers' vulnerability against various biotic and abiotic risks. By reducing the intrinsic risk involved in agricultural production, investments in agricultural R&D can reduce government spending on agriculture by reducing disaster aid payments and subsidies involved in the provision of crop insurance. In comparison, subsidizing crop insurance program does not directly reduce the risk of farm operations, but rather constitutes an *ex post* cash redistribution to mitigate the negative consequences of realized risks. As stated in Pardey and Smith (2017), farm programs such as crop insurance simply “slice up the agricultural pie”, while agricultural R&D activities will “expand the overall size of the agricultural pie” to bring benefits to farmers, agribusinesses and taxpaying consumers. Both R&D activities and farm program subsidies provide risk protection for agriculture, therefore making cost-effective policy choices requires allocating limited public funding optimally among the portfolio of risk management tools to reduce agricultural risks and stabilize farmers’ incomes. To achieve these outcomes, it is critical that policy makers fully understand the diverse characteristics and spatio-temporal dynamics of different risks and the associated risk management behaviors farmers choose.

Under the broad topic of agricultural risk management, I will focus on understanding the impact of various agricultural risks on farmers’ risk management strategies from a spatial bio-economic perspective. There is a large body of literature that studies the nature and consequences of agricultural production risks, but few, if any, of these studies differentiate among different types (e.g., biotic versus abiotic) of risks. Failing to make this distinction may result in socially (and privately) costly decisions regarding the relative effectiveness of various agricultural policies and technological options in dealing with risk.

In this study I differentiate between the biotic and abiotic risks involved in the process of agricultural production and assess their distinctive crop production and risk management consequences. Furthermore, my dissertation takes into consideration the geographically sensitive nature of various agricultural risks and mitigation strategies and investigates their impacts using a spatially explicit approach.

Specifically, Chapter 2 investigates the history of wheat varieties planted in the United States. I quantify and characterize the trend in U.S. wheat biodiversity since 1919 using a new compilation of state-specific evidence on the adoption of wheat varieties and the ancestral pedigree of each of these varieties. Understanding the changing spatio-temporal structure of the biodiversity within modern agricultural ecosystems provides important policy guidance on achieving sustainable agricultural production outcomes in the context of various agricultural risks. Chapter 3 analyzes the crop varietal use implications of various biotic and abiotic risks on U.S. wheat farmers, wherein the adoption of new crop varieties changes the production risk exposure faced by these farmers. The implication of this finding gives insights for public and private sector varietal development and deployment strategies so they keep pace with the ever-changing biotic and abiotic risks threatening production agriculture. Chapter 4 studies the impacts of biotic risks and abiotic risks on farmer's demand for crop insurance, and explores the implications of these different risk profiles on crop insurance purchases.

Overall, this dissertation provides an in-depth investigation of various aspects of modern agricultural risk management from a bio-economic, spatially-sensitive perspective, and contributes substantially to the development of socially and economically viable farm programs that help secure U.S and global food supply under risks.

Chapter 2: Agro-Biodiversity: The Spatio-Temporal Dynamics of U.S. Wheat Varieties

2.1 Introduction

Improving agricultural production in a sustainable fashion is essential to ensuring global food security over the long haul. There are growing research and policy interests in valuing the role of biodiversity for agricultural sustainability. According to the Millennium Ecosystem Assessment (2005) report, human-dominated ecosystems, such as crop and livestock productions, have grown significantly in both overall area and per unit area productivity. The first and foremost value of agricultural ecosystems is to satisfy basic human needs for food and livelihood security. Unlike natural ecosystems, agricultural ecosystems are characterized by pervasive human intervention and the unnatural selection of plant species growing within the system (Fowler 1994). For eons, farmers, not scientists, determined the selection and preservation of diverse agricultural crops. Varieties were, and still are, selected in consideration of human needs and their ability to be grown under the specific economic and ecological conditions that prevail in a particular place and for a particular time (season).

Expansion of agricultural cropland is usually accompanied by conversion of natural habitat, which leads to reduction in local native biodiversity. Preservation of biodiversity within agroecosystems has become increasingly challenging as agricultural production has intensified. Most notably, the number of plant species grown as food crops in agricultural landscapes is rather limited. In fact, the world’s population relies on only about 103 plant species for 90 percent of its food crops (Thrupp 2000). Globally, on a daily basis, more than 42 percent of the calories consumed by humans are sourced from only three major staple crops–rice, wheat and maize (FAO 2013; Pardey et al. 2014). In addition to the alarmingly narrow selection of food crop species, there are further concerns about genetic erosion within modern agriculture given the high degree of genetic uniformity where only a handful of varieties tend to dominate each major crop species (National Research Council 1972; Fowler and Mooney 1990; Thrupp 2000; Smolders 2006).

The concern is that a reduction in genetic diversity leads to genetic vulnerability, whereby most of the cultivated varieties of a given crop species become susceptible to certain biotic and abiotic stresses due to similarities in their genotypes (Singh 2002). Historically, several examples of severe economic loss and suffering have been ascribed to genetic uniformity, such as the potato famine of Ireland during the 19th century (Donnelly 2002), Southern corn leaf blight of the U.S. in 1970 (National Research Council 1972), wheat stem rust epidemics in the U.S. during the 1900-1950s period (Kolmer 2001) and the recent outbreak of widely virulent races of the stem rust pathogen in Africa (i.e. Ug99 lineage races) (Singh et al. 2011). Reducing the risk of genetic vulnerability through preservation of biodiversity, while still affording farmers (and consumers) the benefits that come with the use of improved crop varieties, poses a great challenge to modern agriculture.

The preservation of biodiversity within agroecosystem encompasses multiple levels, spanning the gamut from genes, to plant populations, crop species and entire ecosystems. At the ecosystem and species levels, preserving agroecosystem biodiversity means maintaining the balance of various plant, animal and microorganism species to promote an ecosystem that is beneficial for food production. At the sub-species level, increasing biodiversity involves the deployment of a diverse collection of varieties that vary in their genetic, phenotypic, and physiological characteristics. With the widespread adoption of high yielding varieties for major crops since the advent of the Green Revolution in the 1960s, modern agriculture practice is commonly believed to lead to a reduction in on-farm biodiversity that are associated with monoculture cropping practices (Thrupp 2000; Day-Rubenstein et al. 2005; Smolders 2006; Keneni et al. 2012). For example, Thrupp (2000) reports that the number of rice varieties growing on farmers' fields was greatly reduced in Bangladesh, Indonesia, Philippines and India, where large numbers of landraces were replaced by high yielding crop varieties during the Green Revolutions.

However, some studies argue that the reduction in the number of varieties in use does not necessarily lead to genetic erosion or genetic vulnerability (Smale 1997; Smale et al. 1998; Wood and Lenné 1997). In fact, modern agriculture may enable more fine-grained crop adaptation to varying abiotic and biotic stresses via modern breeding methods that can enhance genetic variation and associated physiological traits. Smale (1997) showed that the genetic backgrounds or pedigrees of many modern wheat varieties incorporate a rich tapestry of landraces. Improved varieties can also help reduce genetic vulnerability given that each variety may contain distinct characteristics that make it suitable for specific soil and climate conditions, so planting different varieties in different locations can help stabilize yield, reduce farm risks and promote ecosystem services (Hajjar et al. 2008; Gollin 2006). For example, Mulumba et al. (2012) performed on-farm experiments in Uganda and discovered that an increased diversity of crop varieties was associated with a reduction in pest and disease damage across different sites, thus supporting the argument of using crop varietal diversity as a risk-mitigating strategy for farmers.

In the United States, the National Research Council's committee on Genetic Vulnerability recommended that breeders and farmers increase the number of varieties of crop species and widen the genetic diversity among released cultivars and breeding materials to alleviate the risks associated with increased genetic uniformity (National Research Council 1972; National Research Council 1993). Efforts to breed in greater diversity has reduced the genetic vulnerability of major crops in the U.S. since 1970 according to a survey conducted by Duvick (1984). Wheat was first brought to America by explorers and colonizers in the pre-colonial period, so the growing and improvement of wheat crops in the United States did not originate from landraces but rather from varieties already being used in other countries (Ball 1930). Since the first introduction of wheat in America, farmers and breeders have devoted considerable effort in developing and selecting for wheat varieties that had higher yields, improved quality and better disease and pest resistance. Given the absence of indigenous landrace ancestors, the goal of increasing genetic diversity for wheat crops in the United States relies on the continuous efforts of developing new varieties with more diverse genetic background.

Enhancing biodiversity to alleviate genetic vulnerability involves both spatial and temporal dimensions within modern agricultural landscape. Spatial diversity addresses variations among varieties across landscapes from individual farms to county, state, national and even global scale. Varieties with different genetic backgrounds can be planted at different locations. With efforts in breeding for more locally adapted varieties, modern agricultural crops are exhibiting increasing spatial diversity in their physiological and genetic traits to fulfill geographically specialized human needs. Temporal diversity addresses variations among varieties over time, where old crop varieties are eventually discontinued and newer varieties are adopted by farmers. Compared with natural ecosystems, modern agricultural system can change their genetic composition quickly due to the development and adoption of new varieties. In fact, the average life span of a major crop cultivar is usually less than ten years and could well be shorter in the future if changes in the (relative) costs of breeding coupled with new breeding (e.g., gene editing) techniques induce increased private sector activity (see, for example, Duvick 1984; Murphy 2007). Under constant human intervention, the genetic composition of a crop species can be quickly changed across seasons as new varieties are adopted and old varieties discontinued. This human-driven turnover in the genetic background of the agricultural landscape has shown to be an effective approach to protecting crops from the threat of pest infestations and disease epidemics across multiple growing seasons.

Given the importance of genetic diversity in maintaining agricultural productivity, one persistent question is whether genetic diversity in modern agriculture has improved or worsened across space and over time. Among the many published studies on genetic diversity trends in modern agriculture (see, for example, the review by van de Wouw et al. 2010), to the best of our knowledge none have assessed the extent and change in genetic diversity of major crop species from *both* a spatial and a temporal perspective. Characterizing both the spatial and temporal changes in biodiversity allows for a more complete evaluation of genetic vulnerability in modern agriculture and the implementation of effective policies with an eye to agricultural sustainability. This study contributes significantly to the literature by employing a purpose-built, spatially-disaggregated set of data on the use of U.S. wheat varieties spanning an entire century, coupled with comprehensive pedigree information on each of these varieties, to assess the spatio-temporal dimensions of agro-biodiversity in a monoculture production system.

2.2 Data and Methods

2.2.1 Data on wheat varieties in the U.S.

Data on planted area-by-variety were collected for the U.S. wheat crop for the period 1919-2016 by the author and colleagues at the International Science and Technology Practice and Policy (InSTePP) center, University of Minnesota. To validate the data coverage, we compared the sum of these varietal area estimates (per state per year) with total planted acres (per state per year) for corresponding classes of wheat reported by the U.S. Department of Agriculture National Agricultural Statistics Service (USDA-NASS). Wheat crops are divided into three market classes – durum, spring and winter. Table 2-1 and Figure 2-1 summarize the share of area-by-variety data with respect to total planted acres for each wheat market class in major wheat growing states. In general, not all states and all years have area-by-variety data available, and the year and area coverage vary by state. From 1919 to 1984, acreage-by-variety data are reported in the USDA's quinquennial publication on acreage surveys for a total of 42 states. Unfortunately, this publication was discontinued in 1984, and so we turned to the agricultural statistical services within each state to source these data. A total of 24 states ceased the collection of acreage-by-variety data altogether, while the remaining 17 states provided only periodic reports on such data. After 2000, we were able to compile data for 16 states which span the majority of the wheat producing area in the United States, although not all of these states have complete time series. For each market class, the states for which we have area-by-variety data account for around 90 percent of durum acreage, 100 percent of spring acreage, and 80 percent of winter acreage based on the 2013 NASS data. Overall, the area-by-variety data used in this study represent the majority of wheat producing states in the United States with a comprehensive state-year-area coverage.

In addition to acreage-by-variety data, information on each variety's name, market class, and its pedigree were also collected. Varieties often have aliases or different spellings depending on the time and location they were marketed and adopted. To avoid double counting the same varieties with different names across states and over time, we reconciled the aliases of different varieties and standardized the names across all the wheat varieties reportedly used in the United States since 1919. Multiple sources of wheat genetic and pedigree information were used to consolidate varietal names and their pedigrees, including the Genetic Resource Information System for Wheat and Triticale (CIMMYT 2017), the Germplasm Resources Information Network (NGRP 2017), the GrainGenes database (USDA-ARS 2017), and the Plant Variety Protection Office (PVPO 2017). The entire pedigree of each variety and their parents were traced back to either a landrace, a wild accession or a local variety. The pedigree information for a total of 1,443 commercially grown varieties in the United States was collected and processed, which involved reconciling information spanning 2,622 varieties (including non-commercially grown crossing materials) for the final pedigree analysis.

2.2.2 Species-neutral biodiversity measures

A large number of biodiversity measures have been proposed in the disciplines of ecology, genetics, economics, information theory and other sciences (Fisher et al. 1943; Solow et al. 1993; Shannon 2001; Chao et al. 2014). Among them, the most commonly used are so-called "species-neutral" measures, which treat each species in a community as an equally distinct Operational Taxonomic Units (OTUs), regardless of their taxonomic, genetic or functional similarities. Such indexes include a species richness index, the Shannon entropy index (Shannon 2001), and the Gini-Simpson index (Simpson 1949), all of which are special cases of the generalized Tsallis entropy measures (Keylock 2005; Jost 2006), also known as HCDT entropy (Havrda and Charvát 1967; Daróczy 1970; Tsallis 1988). HCDT entropy indexes can be converted into so-called “true diversity” measures. Such measures, also known as the effective number of species or “Hill numbers”, represent the hypothetical number of equally-abundant species that would give the same diversity index value as observed (Hill 1973; Jost 2006). “Hill numbers” do not depend on the functional form of the index and satisfy the replication principle, whereby the index value doubles if each species was divided into two equal new species (Jost 2006; Tuomisto 2012). Thus, Hill numbers allow for a unified and intuitive interpretation of diversity across sites.

To calculate the species neutral HCDT entropy and its corresponding Hill number for each U.S. wheat growing state, I first define a “community” as the collection of wheat varieties planted within a given state in a given year. The total number of wheat varieties that has ever been planted by farmers during the entire studied period is designated as N. For a total of S wheat growing states during a total of T time periods, the acreage share for variety i within state s and year t is denoted as p_{ist} $(i = 1,2,..N; s = 1, 2, \dots, S; t = 1, 2, \dots, T)$. Following Jost (2006), the HCDT entropy H and the diversity D formula for a given state s in a given year t with an exponent order of $q \geq 0$ can be defined as following:

$$ {}^{q}_{st}H \equiv \left(1 - \textstyle\sum_{i=1}^{N} p_{ist}^{q}\right)/(q-1) \tag{2.1}$$

$$ {}^{q}_{st}D \equiv \left(\textstyle\sum_{i=1}^{N} p_{ist}^{q}\right)^{1/(1-q)} \tag{2.2}$$

To simplify the notation, we adopt the "deformed logarithms" formalism proposed by Tsallis (1994), which is defined as following:

$$ {}_{st}^{q}H = -\sum_i p_{ist}^{q} \ln_{\mathrm{q}} p_{ist}, \text{ where } \ln_{\mathrm{q}} p_{ist} \equiv (p_{ist}^{1-q} - 1)/(1-q) \tag{2.3} $$

$$ {}_{st}^{q}D = e_q^{{}_{st}^{q}H}, \text{ where } e_q^{{}_{st}^{q}H} \equiv \left[1 + (1-q)\,{}_{st}^{q}H\right]^{1/(1-q)} \tag{2.4} $$

Here, the order q of a diversity index represents its sensitivity to rare species, where more weight is given to the more abundant species with increasing value of q. In fact, rare species are disproportionately weighted for $0 \le q < 1$, while more abundant species are disproportionately weighted for $q > 1$ (Jost 2006). For diversity of order 0, the diversity index ${}^{0}D$ equals the total of number of species N, also known as the species richness index, which is completely insensitive to species abundances. For diversity of order 2, the entropy index becomes the Gini-Simpson index, which weights each species by its *relative* abundance and thus gives disproportionately large weight to the most common species. For the critical diversity of order 1, the entropy and diversity indexes are undefined but their limit as q approaches 1 exist, such that ${}^{1}H$ becomes Shannon entropy and ${}^{1}D$ is the exponential of Shannon entropy:

$$ {}_{st}^{1}H \equiv \lim_{q \to 1} {}_{st}^{q}H = -\sum_{i=1}^{N} p_{ist} \, ln \, p_{ist} \tag{2.5} $$

$$ {}_{st}^{1}D \equiv \lim_{q \to 1} {}_{st}^{q}D = e^{{}_{st}^{1}H} \tag{2.6} $$

For a state with N equally-common species (where each species has relative abundance $1/N$), the diversity measure ${}^{q}D$ always returns a value equal to N. Thus, "true diversity" or "Hill number" ${}^{q}D$ represents the number of equally abundant species that would give rise to the same diversity value (Hill 1973; Jost 2006).

2.2.3 Phylogenetic biodiversity (PD) measures

One apparent limitation of the species-neutral biodiversity measures is that the notion of a distinct Operational Taxonomic Unit (OTU) does not naturally apply to an assessment of diversity *among varieties within a species*. For wheat, new varieties are typically developed by genetic crosses among existing varieties, and thus the contribution of each new variety to the overall crop diversity depends on their relatedness to existing varieties. Commonly used species-neutral biodiversity measures such as species richness and Shannon entropy are unsuitable to differentiate sites growing many genetically similar but nonetheless differentiated (by name) crop varieties from those sites with many genetically distant crop varieties. Thus, characterizing the biodiversity of a crop species in modern agricultural landscapes requires a non-neutral approach, which by construction incorporates the notion of varietal similarities into the measure of diversity.

There has been a growing number of non-neutral biodiversity measures proposed to account for taxonomic, functional or phylogenetic similarities among species within a community, such as Rao's quadratic entropy (Rao 1982), taxonomic cladistics diversity (CD) (Vane-Wright et al. 1991), phylogenetic diversity (PD) (Faith 1992), pure diversity measure (Solow et al. 1993; Solow and Polasky 1994), function diversity (FD) (Tilman 2001) and many others (e.g., Crozier 1992; Weitzman 1992; Warwick and Clarke 1995; Chao et al. 2010; Chiu and Chao 2014). Among these alternatives, one common approach to account for the genetic similarities among biological individuals is the phylogenetic diversity (PD) measure proposed by Faith (1992). This diversity measure is defined as the sum of all the phylogenetic branches along the minimum spanning path to quantify the evolutionary history shared among individuals. Weitzman (1992) points out that a community's diversity value can be represented by the branch length of the hypothetical phylogenetic tree.

Traditional PD measures focus mainly on the presence or absence of a species to measure the overall genetic variation within a community, without taking into account the relative abundance of each species. However, species abundance provides crucial information regarding the composition of the community, especially for agroecosystems where a few popular crop varieties may dominate the majority of the landscape, while numerous other varieties account for comparatively small portions of the overall cropped area. To incorporate both species abundance and species phylogenetic distances, Chao et al. (2010) generalized the traditional phylogenetic measure and proposed a PD measure based on Hill numbers which quantifies "the mean effective number of species," and in so doing unified many of the existing measures of biodiversity.

To calculate a generalized PD, a phylogenetic tree is first constructed based on distances between species of the community. Both molecular markers and pedigree information have been used in major crop genetic diversity studies to derive genetic distances among crop varieties. For this study, we use the Coefficient of Parentage (COP) concept to infer genetic relatedness from pedigree information on all U.S. wheat varieties planted during the period 1919 to 2016. COP calculates the proportion of shared genetic material among varieties based on their pedigrees under the following assumptions: (1) a cultivar inherits half of its genes from each parent; (2) all parental lines are homozygous and homogeneous; and (3) all landraces are unrelated to each other (Murphy et al. 1986). Defining the pair-wise dissimilarity index between variety i and variety j as d_{ij}, we can obtain a pair-wise dissimilarity matrix D for the collection of all wheat varieties over the entire study period in the United States. Based on the pairwise dissimilarity matrix, a phylogenetic tree can be constructed for all U.S. wheat varieties. Using the phylogenetic tree, the generalized PD (denoted as $\bar{H}$) for a community of wheat varieties can then be calculated using Chao et al.'s (2010) methods as:

$$^{q}\bar{H}\,(\bar{T}) = \left[\sum_{i=1}^{B} T_i \times \left(\frac{a_i}{\bar{T}}\right)^{q}\right]^{\frac{1}{1-q}} \tag{2.7}$$

where B is the number of branch segments in the tree, T_i denotes the length of branch i ($i = 1, 2, \ldots, B$), a_i denotes the branch abundance (sum of relative abundance of all species descended from branch i), and $\bar{T} = \sum_{i=1}^{B} T_i a_i$ denotes the mean branch length. For special cases of the order q spanning the entire age of the phylogenetic tree, it is shown that $^{0}\bar{H}(\bar{T})$ becomes the total branch length, which is the traditional Faith's PD; $^{1}\bar{H}(\bar{T})$ can be linked to the generalization of Shannon entropy to incorporate phylogenetic distances; and $^{2}\bar{H}(\bar{T})$ can be linked to Rao's quadratic entropy (Chao et al. 2010; Chiu and Chao 2014). The phylogenetic Hill number is then calculated as:

$$^{q}\bar{D}(\bar{T}) = \frac{^{q}\bar{H}(\bar{T})}{\bar{T}} = \frac{1}{\bar{T}}\left[\sum_{i=1}^{B} T_i \times \left(\frac{a_i}{\bar{T}}\right)^{q}\right]^{\frac{1}{1-q}} \tag{2.8}$$

For a state with N equally-common species that are completely distinct from each other along the phylogenetic tree, the diversity measure $^{q}\bar{D}(\bar{T})$ always gives exactly N. Thus, the phylogenetic Hill number $^{q}\bar{D}(\bar{T})$ can be interpreted as the effective number of maximally distinct lineages with equal relative abundance (Chao et al. 2010).

2.2.4 Spatial and temporal diversity decomposition

The species-neutral and generalized PD indexes introduced above are both static measurements of biodiversity for a single community (e.g., a U.S. state, or the U.S. as a whole). However, spatial and temporal variations in the mix of crop varieties are one of the most fundamental features of modern agricultural systems. Thus, decomposing biodiversity into its spatial and temporal components is required in order to better characterize the dynamic changes over space and time in agricultural biodiversity. A growing number of long-term datasets have been utilized to examine spatial and temporal patterns of biodiversity change within ecological systems (Magurran et al. 2010). To the best of our knowledge, this study is the first to incorporate both spatial *and* temporal decompositions into the assessment of the diversity dynamics of a major crop species.

Whittaker (1960) first proposed the decomposition of the overall diversity (γ- diversity) into within-community (α- diversity) and between-community (β- diversity) components using either an additive law or multiplicative law. For spatial decomposition within each time period, each U.S. state can be treated as a separate community, and the variations among different states reflects the spatial diversity across the landscape. For temporal decomposition with each U.S. state, each year can be treated as a separate community and the variations across years reflect the temporal diversity within each state.

Here I first define a community as the collection of varieties planted within a given state for a given year. Then a “spatial metacommunity” is defined as the collection of all communities within a single year (i.e., all states in the U.S. within a given year) and a “temporal metacommunity” is defined as the collection of communities over multiple years within the same state (i.e., all years within a given state). With these definitions of spatial and temporal metacommunities, following Marcon et al. (2014), the total species neutral HCDT entropy (γ- entropy) for a metacommunity ${}^{q}H_{\gamma}$ can be decomposed as:

$$ {}^{q}H_{\gamma} = {}^{q}H_{\alpha} + {}^{q}H_{\beta} = \sum_m w_m {}_{m}^{q}H_{\alpha} + \sum_m w_m {}_{m}^{q}H_{\beta} \tag{2.9} $$

where α- and β- entropies for the metacommunity (i.e., ${}^{q}H_{\alpha}$ and ${}^{q}H_{\beta}$) are the weighted sums of local entropies within each community (i.e. ${}_{m}^{q}H_{\alpha}$ and ${}_{m}^{q}H_{\beta}$). The weight w_m adjusts for sample size differences among communities, which is commonly defined as $w_m = n_m/N$ where n_m is the number of individuals in a local community and N is the total number of individuals for a metacommunity. The α- and β- entropies for a community are calculated as:

$$ {}_{m}^{q}H_{\alpha} = -\sum_i p_{im}^{q}\, ln_q\, p_{im} \tag{2.10} $$

$$ {}_{m}^{q}H_{\beta} = \sum_i p_{im}^{q} \ln_{\mathrm{q}} \frac{p_{im}}{p_i} \text{ where } p_i = \sum_m p_{im} \tag{2.11} $$

Similarly, as a linear transformation of generalized entropy, the generalized PD for the metacommunity ${}^{q}\bar{H}_{\gamma}(T)$ can be decomposed as:

$$ {}^{q}\bar{H}_{\gamma}(T) = {}^{q}\bar{H}_{\alpha}(T) + {}^{q}\bar{H}_{\beta}(T) \tag{2.12} $$

where

$$ {}^{q}\bar{H}_{\gamma}(T) = \sum_k \frac{T_k}{\bar{T}}\, {}_{k}^{q}H_{\gamma} \tag{2.13} $$

$$ {}^{q}\bar{H}_{\alpha}(T) = \sum_m w_m \sum_k \frac{T_k}{\bar{T}}\, {}_{k}^{q}H_{\alpha} \tag{2.14} $$

$$ {}^{q}\bar{H}_{\beta}(T) = \sum_m w_m \sum_k \frac{T_k}{\bar{T}}\, {}_{k}^{q}H_{\beta} \tag{2.15} $$

The corresponding decomposition of the diversity index ${}^{q}\bar{D}_{\gamma}(T)$, also known as phylogenetic Hill number, is then obtained as:

$$ {}^{q}\bar{D}_{\gamma}(T) = {}^{q}\bar{D}_{\alpha}(T)\, {}^{q}\bar{D}_{\beta}(T) \tag{2.16} $$

where

$$ {}^{q}\bar{D}_{\gamma}(T) = e_q^{{}^{q}\bar{H}_{\gamma}(T)} \tag{2.17} $$

$$^{q}\overline{D}_{\alpha}(T) = e_q^{\,^{q}\overline{H}_{\alpha}(T)} \tag{2.18}$$

$$^{q}\overline{D}_{\beta}(T) = e_q^{\frac{^{q}\overline{H}_{\beta}(T)}{1+(1-q)^{q}\overline{H}_{\alpha}(T)}} \tag{2.19}$$

Depending on the grouping of communities into a given "spatial metacommunity" or a "temporal metacommunity", formula (2.16)-(2.19) allows us to decompose diversity into its respective spatial or temporal dimensions. Essentially, for a metacommunity (i.e., a collection of local communities), the overall γ-diversity is decomposed into an average local community diversity (α-diversity) and a measure of the effective number of communities (β-diversity).

Intuitively, for a given year in the United States with an overall phylogenetic diversity index value γ, the α-diversity component of this "spatial metacommunity" indicates the average diversity of wheat varieties growing within a state (i.e. the average effective number of varieties from maximally distinct lineages with equal relative abundance in a state), while the β-diversity component of this "spatial metacommunity" indicates the effective number of distinct states (i.e., the equivalent number of states that each has α effective number of varieties that are distinct from each other). Similarly, for a "temporal metacommunity" (i.e., multiple years for a given state) with an overall phylogenetic diversity γ, the α-component indicates the average diversity of wheat varieties growing each year in this state, while the β-component indicates the effective number of distinct years (i.e., the equivalent number of years where each has α effective number of varieties that are distinct from each other). Using a unique long-run panel dataset for a major crop species, such spatial and temporal decompositions allow us to better understand the impact of crop varietal turnover on modern agricultural genetic diversity and address key questions concerning 1) the overall trends in the phylogenetic diversity of the U.S. wheat crop; and 2) changes in either the spatial or temporal dimensions of the U.S. wheat crop diversities over the past century.

2.3 Empirical Results

2.3.1 Age structure of U.S. wheat varieties

In our compilation of wheat area-by-variety data, there are a total of 127 durum, 496 spring and 1,031 winter wheat varieties during the period of 1919-2016. The annual average number of reported durum, spring and winter wheat varieties grown each year during the past thirty years (specifically 1986-2016) are 25, 67 and 148 respectively (Table 2-2). In the United States, winter wheat is the most common wheat class and was planted on more than 70 percent of the total wheat area in 2012 (NASS 2018). Spring wheat follows, with 24.8 percent of the planted area in 2012, and durum wheat has 4.4 percent of the acreage.

To account for the overall acreage differences among different market classes, we calculated the varietal count per unit area (i.e., the average number of varieties per million acres of wheat area, Table 2-2). Notably, durum wheat—which has the lowest overall and yearly average number of varieties—, actually represents the highest varietal count per unit area among all three wheat market classes. For example, durum wheat has an average of 11 varieties per million acres per year, almost twice as many as either spring or winter wheat, which both average around 6 varieties per million acres per year (Table 2-2).

To assess the changing age structure among wheat varieties, Figure 2-2 plots the number of varieties reported each year within each age group (i.e., new, 2-5 years, 6-10 years, 11-15 years, and >15 years). Here, the age of a variety is calculated as the number of years following its first year of reported planting anywhere in the United States. The average number of new varieties planted each year was 3, 8, and 18 for durum, spring and winter wheat, respectively, during the period 1986-2016, while the majority of wheat varieties were under 15-years-old across all three market classes (Table 2-2, Figure 2-2). For winter wheat, there was an average of 115 varieties below 15-years-old reported each year, almost four times more than the number of varieties that were more than 15-years-old. Durum and spring wheat also had much higher numbers of younger (below 15-years-old) than older (more than 15-years-old) varieties during the past three decades.

In general, the age group of "2-5 years" encompasses the largest number of varieties, with an average of 7 (28.0 percent), 23 (34.3 percent) and 43 (29.1 percent) varieties each year for durum, spring and winter wheat, respectively (Table 2-2). The age structure of U.S. wheat varieties suggests a high rate of varietal turnover since the number of long-lasting varieties (older than 15-years-old) only accounts for less than 25 percent of the total number of varieties planted each year on average. The lower number of varieties within higher age groups indicates that wheat farmers' choice sets of recent wheat varieties is broader but their choice of older varieties is more restricted.

2.3.2 Dynamics of varietal turnover in U.S. wheat

Tracking the history of each variety allows us to explore the dynamics of varietal adoption and disadoption in U.S. wheat. Figure 2-3 depicts the yearly presence and absence status of each wheat variety in the U.S., ordered by their first year of adoption. Each year, there are new varieties being added and older varieties being discontinued. Summary statistics for varietal longevity in the U.S. are reported in Table 2-3. Of note, varietal longevity is highly variable, depending on the variety in question. For example, the winter wheat variety “Cheyenne” was reported almost every year for a period of 80 years during 1934-2013, with acreage ranging from a peak of almost 2.5 million acres per year during 1959-1964 to less than 5,000 acres in 2013. In fact, there are a total of 425 wheat varieties (36 durum, 115 spring, and 274 winter) in the U.S. that have lasted more than 15 years. On the other hand, there are more than 200 wheat varieties that are reported to have been planted in only one year ever. The number of varieties that are planted less than five years exceeds 500. These varieties have failed to withstand farmer’s selection criteria and establish themselves as longer lasting varieties. On average, the longevity for durum, spring and winter wheat varieties are 11.5, 10.7 and 11.1 years, respectively, while the overall average wheat varietal longevity is approximately 11 years in the U.S. (Table 2-3).

In addition to changes in farmer varietal choices each year, the area planted to each variety also changes over time. The time series on total area planted for the leading wheat varieties in the U.S. are illustrated in Figure 2-4, where leading wheat varieties are defined as varieties ranked among the top three in terms of total area planted in a given year. There is a regularity in the dynamics of varietal use. In general, each of the top varieties is sown to a comparatively small acreage at first, then gradually establishes as a dominant variety for a few years, and then declines in planted acreage before eventually being discontinued. Comparing the top varieties during the most recent decade with those from earlier decades, we can see that, for all three market classes of wheat, the top varieties are almost composed of completely different collections of varieties every ten years or so. Thus, the landscape of wheat varieties planted in the U.S. is constantly in flux. From one season to another, wheat farmers are making changes to both their choice of variety and the area allocated to each variety.

2.3.3 Species-neutral biodiversity measures

Here we treat each U.S. state as a distinct community, where the area planted to each wheat variety varies both spatially (i.e., across states) and temporally (i.e., over years). Leading variety acreage dominance serves as a straightforward indicator of the uneven area distribution among varieties, as shown in Figure 2-5. In general, the acreage shares attributed to the top five contemporary wheat varieties within each state declines over time, thus indicating that the dominance of major wheat varieties weakens over time and wheat farmers are expanding their choice set of major varieties.

The HCDT diversity indexes allow direct comparisons of the "effective number of species" (or "true diversity") among different communities, which can be interpreted as the hypothetical number of species with equal abundance that would yield the same diversity index value. For HCDT biodiversity measures, the choice of exponent order q affects the weights assigned for common and rare species, so the three most commonly used exponent orders are used in this study, which include varietal Richness ($q = 0$), Shannon's index ($q = 1$), and Gini-Simpson's index ($q = 2$), respectively. These diversity indexes are plotted over time for each state during 1919-2016 in Figure 2-6. The summary statistics for these indexes are reported in Table 2-4 by market class for each of the major wheat producing states. Due to the incomplete area-by-variety data coverage across states and over time, we scaled the HCDT indexes based on the corresponding area coverage for each state-year combination to obtain area-normalized indexes to allow comparison among states and over time.

The varietal richness index (Figure 2-6) indicates that the number of varieties grown in each state varies greatly among states and over time. The highest yearly number of varieties are reported during the early 1980s for many states (e.g., Colorado, Kansas, Montana, Nebraska, Oklahoma and South Dakota), with the exception of Washington which reached the highest varietal richness in 2010 with 54 varieties reported. Summary statistics on state level varietal richness indexes by market class are reported in Table 2-4. For durum wheat, both Montana and North Dakota have an average of 12 varieties planted each year, higher than California, which has an average of 8 varieties each year. For spring wheat, Minnesota has the highest average number of varieties reported each year (26 varieties), followed by Montana (22 varieties) and North Dakota (21 varieties). For winter wheat, Texas has the highest average number of varieties reported each year (42 winter varieties), followed by Kansas (32 varieties), Oklahoma (32 varieties) and Washington (28 varieties).

Shannon's index ($q = 1$) and Gini-Simpson's index ($q = 2$) both exhibit increasing but fluctuating trends overtime across different states as shown in Figure 2-6, although their magnitude of the fluctuations for these indexes was much less pronounced than the varietal richness index. By definition, these indexes can be interpreted as the effective number of evenly distributed varieties that would yield the same diversity level. Lower index values compared with the varietal richness index indicates that the area in wheat is not uniformly planted to all varieties. Differences among the varietal Richness, Shannon's and Gini-Simpson's indexes indicate that the acreage planted to each particular variety may change markedly from year to year. In other words, U.S. wheat varietal use (i.e., both the rate of turnover and the extent of use) is quite volatile, resulting in frequent changes in the pattern of planted wheat varieties. On average, Montana and Washington, which have the highest varietal richness indexes, also have the highest diversity indexes (Table 2-4).

2.3.4 Spatial and temporal genetic variations among U.S. wheat varieties

Using the pedigree information we compiled, the Coefficient of Parentage (COP) between each pair of wheat varieties in the U.S. was calculated according to the method described in Murphy et al. (1986). Based on the COP matrix, a phylogenetic tree was then constructed, where the genetic distance between each pair of wheat varieties is represented by the branch length between them. On the temporal dimension, the presence or absence data for wheat varieties planted in the U.S. each year were plotted along with the phylogenetic tree to illustrate the dynamics of phylogenetic variation over time (Figure 2-7).

The three market classes for wheat differ in their clustering locations along the phylogenetic tree. For durum wheat, most of the varieties are genetically concentrated within a closely clustered region on the phylogenetic tree. However, durum wheat varieties appear to change their genetic relatedness during the early 2000s, where varieties planted after 2000 are different from those planted before 2000. Spring wheat varieties cluster at two different locations along the phylogenetic tree, implying possibly two distinct groups of spring wheat varieties in terms of their genetic background. Overall, winter wheat varieties exhibit a much more diverse genetic background than durum or spring wheat, with varieties ranging across the entire phylogenetic tree. However, the genetics of winter wheat varieties constantly change over time, with expansion and abandonment of varieties in certain regions along the phylogenetic tree. As a general trend, the phylogenetic variation among wheat varieties in the United States increases over time, as shown by the expanding coverage along the phylogenetic tree over time.

The presence or absence data for every wheat variety planted within each state were also plotted along with the phylogenetic tree to obtain a heat map to illustrate the spatial variation in wheat varieties among states (Figure 2-8). Among the three durum wheat states, Montana and North Dakota share similar durum wheat varieties, both of which are quite distinct from the durum wheat varieties planted in California. For spring wheat, the varieties planted by the Midwestern states (specifically, South Dakota, Minnesota, and North Dakota) cluster at different locations on the phylogenetic tree from those planted within the Pacific North West states (Oregon and Washington). Interestingly, spring wheat varieties planted in Montana resemble the varieties from the Midwest states, while varieties from Idaho, an adjacent state to Montana within the Rocky Mountains region, more resemble the varieties from the Pacific North West states that lay to its west than its adjacent eastern neighbor.

For winter wheat, there are more spatial variation across states. States within the Great Plains (including Texas, Nebraska, Wyoming, Colorado, Oklahoma, and Kansas) appear to plant phylogenetically similar varieties, which are different to the varieties planted in the Midwest region or the Pacific North West region. In addition, Indiana and Kentucky cluster as a group with similar wheat varieties. California is unique in terms of the winter wheat varieties planted there, since many of the winter wheat varieties in the state are genetically spring type wheats but are sown in the autumn (California Wheat Commission 2017). In fact, as shown in Figure 2-8, some of the winter wheat varieties in California are genetically similar to Midwestern spring wheat varieties.

2.3.5 Phylogenetic biodiversity (PD) measures

Based on information from the phylogenetic tree, PD indexes are calculated for each of the major wheat producing states in the U.S. during the 1919-2016 period. Summary statistics of the PD indexes by market classes are reported in Table 2-5. Overall, PD indexes are slightly smaller than their species neutral counterparts (Table 2-4) because PD indexes weight each species according to their phylogenetic similarities with other species, which results in a smaller effective number of maximally distinct species. Nonetheless, both PD and HCDT indexes reveal similar diversity rankings. For example, California has the lowest level of diversity among all three durum states according to both phylogenetic and species-neutral diversity indexes. For spring wheat, Minnesota has the highest diversity indexes while Oregon and South Dakota have the lowest diversity indexes on average. Texas and North Dakota rank as the highest and lowest winter wheat diversity states, respectively, according to both HCDT and PD indexes.

To further compare PD and HCDT indexes, Figure 2-9 plots the PD indexes (order 1) against the species neutral Shannon's Diversity index (order 1). For all states, PD indexes (order 1) are always smaller than the corresponding Shannon's Diversity index and both types of indexes exhibit similar trends over time. The overall, and dominant, trend is for wheat diversities to be increasing over time in all major wheat growing states for all three market classes. For winter wheat, many states—including Kansas, Kentucky, Montana, Nebraska, Oklahoma, Texas and Washington— exhibit large increases in diversity since 1990, while some of the smaller wheat growing states, such as Indiana, Oregon and Wyoming, experience stagnant or decreasing diversity over the long run. The diversity indexes of spring wheat are generally comparable with those of winter wheat within states growing both market classes, such as those in South Dakota and Washington, although North Dakota seems to have slightly higher spring wheat diversity than winter wheat diversity. Durum wheat diversity indexes are lower than winter wheat in California and Montana but fluctuate in between winter and spring wheat in North Dakota.

2.3.6 PD temporal decomposition

Treating the collection of all years for a single state as a "temporal metacommunity," the overall γ-diversity for this metacommunity can be decomposed into its within-community α-diversity—which captures the average effective number of varieties planted each year in a state—and its temporal β-diversity—which measures the effective number of distinct years for a state—components. To represent these temporal decomposition of diversities, Figure 2-10 plots the α-diversity (within-community) on the x-axis and temporal β-diversity (between-community) on the y-axis for each state, where the overall rectangle area represents the metacommunities' overall γ-diversity.

For winter wheat, there are large differences in terms of α-, β- and γ- diversities across states. As the highest overall γ-diversity state, Texas has the highest within community α-diversity and the third highest temporal β- diversity, which can be interpreted as that state having more than 11 effectively distinct varieties planted each year and more than 20 distinctly different years during the 98-year period of 1919-2016. In contrast, Wyoming has the lowest overall γ-diversity, the lowest α-diversity, and the lowest temporal β-diversity, with an average of just 4 effective varieties grown each year and less than 10 distinct years. In terms of α-diversity, the top states include Texas, Washington and Kansas, all of which plant more than 9 effective varieties each year on average. For temporal β-diversity, Kentucky has the highest temporal β-diversity with the effective number of years being 30 during 1919-2016, suggesting a very rapid rate of varietal turnover, which averaged 3.3 years during the study period.

For spring wheat, Minnesota has the highest overall γ-diversity with more than 6 effective varieties each year, and 30 distinct years. Washington and South Dakota has the highest α-diversity and β-diversity respectively. In Washington, the spring wheat α-diversity is smaller than its winter wheat α-diversity, with a difference of about 2 effective varieties. In South Dakota, its spring wheat β-diversity is higher than winter wheat, indicating a faster rate of turnover for spring versus winter wheat in that state. Spring wheat in North Dakota has higher α-, β- and γ-diversities than the other two market classes, suggesting higher effective number of varieties and faster replacement rates for spring wheat in that state.

For the three durum wheat states, Montana and North Dakota plant more than 5 effective varieties each year, higher than California which only has about 4 effective varieties each year. The temporal β-diversity are similar among the three states, all of which has approximately 10 distinct years, indicating an average variety turnover time of 9.8 years during 1919-2016.

2.3.7 PD spatial decomposition

To characterize the spatial variation of wheat varieties across states, the collection of all major wheat growing states in the United States for each year is treated as a spatial metacommunity. In this case, the γ-diversity represents the overall diversity in the United States, which can be decomposed into within-community α-diversity—representing the average effective number of varieties in a state—, and the spatial β-diversity,—which represents the effective number of distinct states in the United States. For the three market classes of wheat in the United States, their overall γ-diversity and its α- and β-decompositions are plotted over time in Figure 2-11. Overall, the line graphs show that the diversity indexes are generally increasing over time for all three market classes of wheat in the United States, where winter wheat has the highest overall γ-diversity followed by spring wheat. Winter wheat and spring wheat have similar α-diversity indexes over time, suggesting that the state-level wheat varietal diversities are similar among these two market classes. However, winter wheat has much higher spatial β-diversities than spring wheat, consistent with the fact the winter wheat is grown in more states over larger geographic areas than spring wheat in the United States. In general, higher spatial variations across states drive the higher overall diversity for winter wheat in the United States. With only three major durum wheat states, the spatial β-diveristy and overall γ-diversity for durum are the lowest among the three market classes. Interestingly, during the period spanning the mid-1980s to the mid-1990s, the average state-level α-diversities for durum wheat reached levels similar to those of winter and spring wheat, although α-diversities for winter and spring wheat subsequently increased, while for durum wheat the index declined slightly. The overall γ-diversities for the U.S. wheat crop is heavily influenced by the spatial β-diversities, suggesting that spatial variations among states are an important contributing factor to the overall diversity of the wheat population (across each of the three market classes).

2.4 Discussion

To address growing concerns about the loss of biodiversity and the sustainability of modern agricultural cropping systems, this study utilizes a unique data set on wheat varietal use in the United States to characterize varietal diversity in a modern agricultural landscape from both a spatial and a temporal perspective. With a time period spanning almost a century, and a spatial coverage of all major wheat growing states in the United States, this study represents a first attempt at depicting a comprehensive history of major crop varietal diversity in a modern agricultural system. The results of this study show that the diversity of wheat crops in the United States is increasing over time for most states. Winter wheat has the highest number of varieties planted in the United States each year with an average of 148 varieties per year, followed by spring wheat (67 varieties per year) and durum wheat (25 varieties per year). Every year there are new varieties being adopted by farmers and for most years the majority of the varieties grown by farmers are less than 15 years old. However, the commercial longevity of any given variety ranges anywhere between one to over eighty years. Major wheat varieties change from year to year and usually follow the trend of starting with a low acreage, peaking in a few years, then declining over time. As a result of constant varietal turnover, the portfolio of wheat varieties grown by farmers nowadays are substantially different from varieties grown just one or two decades ago, and distinctly different from the varieties grown in the distant past.

In addition to area-by-variety data, this study also takes into account phylogenetic similarities among varieties by incorporating pedigree information for each wheat variety to calculate their phylogenetic diversity. Over time, the phylogenetic diversity of wheat varieties in the United States has increased, as shown by the expanding coverage along the phylogenetic tree from 1919 to 2016. Winter wheat varieties cover more branches along the phylogenetic tree than spring wheat and durum wheat, suggesting higher genetic variation among winter wheat varieties than the other two market classes.

Spatially, wheat varieties grown in different states tend to vary according to their geographic location. Spring wheat varieties grown in Midwestern states differ from those grown in states in the Pacific North West in terms of their phylogenetic similarities. For winter wheat, states within the Great Plains seem to grow similar varieties, which differ from varieties in the Midwest or the Pacific North West regions. An assessment of state-level phylogenetic diversity also reveals a similarly increasing trend in varietal diversity over time.

Decomposing the overall γ-diversity for all years in a given state allows us to disentangle the changes in diversity attributable to changes in the average state-level diversity (α-diversity) versus those attributable to varietal turnover (β-diversity). In addition to the overall γ-diversity differences, the levels of α-diversity and β-diversity also vary greatly across states. For winter wheat, high α-diversity states include Texas, Washington, and Kansas, all of which have at least 10 effective varieties, more than twice as many as states such as Wyoming and North Dakota that have low α-diversity. Kentucky has the highest β-diversity for winter wheat (30 effective years), indicating a very high rate of varietal turnover. For spring wheat, both North Dakota and Washington have relatively high α-diversities (about 8 effective varieties), although their β-diversities (about 15 effective years) are relatively low compared to the top states such as South Dakota (close to 40 effective years). In general, durum wheat has lower overall diversities as well as lower α-diversity and β-diversity components, compared with the other two market classes.

Spatial decomposition distinguishes the overall γ-diversity of a metacommunity into within-state (α-diversity) and between-state (β-diversity) variations. For wheat varieties in the United States, the overall γ-diversities and their α- and β- components all trend upwards over time. Winter wheat shows the highest overall γ-diversities, which is mainly driven by the spatial β-diversity components as a result of high spatial variations across states. In fact, the effective states for winter wheat are more than twice as many as the number of effective states for spring wheat, and more than four times as much as durum wheat for most years. From the perspective of state-level α-diversity, winter wheat and spring wheat have similar effective number varieties each year, suggesting that wheat farmers for both market classes are comparable in terms of state-level varietal diversity although winter wheat varieties are grown in larger regions and vary more across states.

Contrary to the common belief that genetic diversity in modern agriculture has been declining over time, varietal diversity in the U.S. wheat crop has been generally increasing over time, both within states and among states. Our results show that U.S. wheat farmers are not only planting a more diverse collection of varieties each year, but they are also changing the composition of their variety collections over time. Spatial and temporal β-diversities vary depending on the particular states and years being examined, but both dimensions of diversity contribute towards an increase in the overall diversity of the U.S. wheat crop.

Table 2-1. Area-by-variety data coverage for major U.S. wheat producing states during 1919-2016

Wheat Class	State	Number of years reporting data	Planted acres covered during reported years		
			min	max	mean
				(percent)	
Durum	California	35	32.7	100.0	92.0
	Montana	38	81.3	100.0	94.5
	North Dakota	43	39.3	100.0	92.2
Spring	Idaho	41	47.2	100.0	83.6
	Minnesota	30	82.8	100.0	98.3
	Montana	45	57.0	100.0	92.6
	North Dakota	43	79.7	100.0	94.1
	Oregon	40	77.4	100.0	94.5
	South Dakota	21	64.2	100.0	90.0
	Washington	41	62.2	100.0	94.6
Winter	California	43	57.9	100.0	89.2
	Colorado	45	68.7	100.0	88.7
	Idaho	41	66.6	100.0	88.2
	Indiana	31	39.1	100.0	83.9
	Kansas	43	69.7	100.0	92.1
	Kentucky	21	67.1	99.8	83.5
	Montana	45	75.0	100.0	92.2
	Nebraska	43	69.0	100.0	93.9
	North Dakota	35	49.6	100.0	85.4
	Oklahoma	37	64.0	100.0	88.7
	Oregon	40	64.2	100.0	93.3
	South Dakota	23	46.5	100.0	83.4
	Texas	22	63.0	100.0	88.3
	Washington	41	76.9	100.0	95.2
	Wyoming	41	58.6	100.0	92.7

Note: The area-by-variety data were reported every 5 years during 1919-1984 and every year after 1985. So the maximum number of years for data reporting during the period 1919-2016 is 46 years.
Source: Developed by author.

Table 2-2. Summary statistics on the number of wheat varieties planted each year

Variables	Durum			Spring			Winter		
	min	**max**	**mean**	**min**	**max**	**mean**	**min**	**max**	**mean**
					(# of varieties)				
per year	15	33	25	42	97	67	83	202	148
per million acres per year	5	20	11	4	8	6	4	9	6
per year by age group									
New	1	6	3	3	20	8	3	34	18
2-5 years	2	10	7	15	36	23	26	58	43
6-10 years	3	11	7	9	24	16	13	46	34
11-15 years	1	8	4	3	12	9	10	30	20
>15 years	1	9	5	3	19	11	13	49	33

Note: Only data after 1986 is included in this summary table because data during 1919-1984 is not reported every year but every five years.
Source: Developed by author.

Table 2-3. Summary statistics on the longevity of wheat varieties in the U.S.

Variety Longevity	**All Wheat**	***By market classes***		
		Durum	***Spring***	***Winter***
		(Number of varieties)		
1 Year	208	23	69	116
2-5 Years	298	20	99	179
6-10 Years	370	32	95	243
11-15 Years	353	16	118	219
>15 Years	425	36	115	274
Total	**1654**	**127**	**496**	**1031**

Note: The average longevity for all wheat varieties is 11.06 years, where durum wheat has an average longevity of 11.51 years, spring wheat 10.73 years and winter wheat 11.16 years.
Source: Developed by author.

Table 2-4. Summary statistics on the species-neutral diversity indexes for major U.S. wheat producing states during 1919-2016

Market Class	**State**	**Richness**		**Shannon**		**Gini-Simpson**	
		mean	*sd*	*mean*	*sd*	*mean*	*sd*
Durum	California	7.71	3.40	4.80	2.03	3.97	1.86
	Montana	12.05	4.60	6.21	2.11	4.63	1.74
	North Dakota	12.16	3.67	6.65	2.35	5.15	1.82
	Total	**10.84**	**4.39**	**5.96**	**2.29**	**4.63**	**1.85**
Spring	Idaho	14.28	6.35	8.22	4.11	6.41	3.86
	Minnesota	26.19	12.66	8.45	4.77	5.67	3.52
	Montana	21.62	7.24	9.24	3.92	6.35	2.81
	North Dakota	20.66	7.61	9.67	4.31	6.69	3.18
	Oregon	13.73	3.34	5.90	1.87	4.11	1.65
	South Dakota	13.90	10.47	6.51	3.97	4.94	2.80
	Washington	19.86	7.21	9.03	4.06	6.07	3.18
	Total	**18.73**	**8.88**	**8.29**	**4.10**	**5.83**	**3.16**
Winter	California	19.50	5.10	8.25	3.21	6.09	2.43
	Colorado	18.22	9.76	8.01	3.62	5.59	2.89
	Idaho	19.36	7.72	10.77	5.39	7.71	3.85
	Indiana	12.97	7.32	6.12	2.40	4.69	1.98
	Kansas	32.44	17.41	12.07	5.39	8.32	4.00
	Kentucky	17.97	6.73	9.10	4.66	6.63	3.52
	Montana	21.80	7.11	9.53	4.18	6.75	2.98
	Nebraska	19.92	7.90	11.23	5.39	8.43	4.69
	North Dakota	8.51	4.96	5.28	3.08	4.09	2.39
	Oklahoma	31.97	13.07	10.91	5.69	6.64	3.78
	Oregon	19.17	3.57	5.22	2.15	3.53	1.74
	South Dakota	13.24	8.83	6.56	3.97	4.86	3.12
	Texas	41.86	28.75	18.02	13.09	11.76	7.85
	Washington	27.97	11.80	11.58	5.17	7.61	3.26
	Wyoming	12.36	5.21	4.68	2.01	3.07	1.53
	Total	**20.86**	**13.18**	**8.98**	**5.72**	**6.28**	**3.96**

Source: Developed by author.

Table 2-5. Summary statistics on the phylogenetic diversity (PD) indexes for major U.S. wheat producing states during 1919-2016

Market		PD0		PD1		PD2	
Class	**State**	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
Durum	California	7.55	3.36	4.73	2.02	3.92	1.84
	Montana	10.98	4.21	5.40	1.84	3.81	1.31
	North Dakota	10.85	3.20	5.65	1.97	4.10	1.49
	Total	**9.94**	**3.90**	**5.30**	**1.96**	**3.95**	**1.54**
Spring	Idaho	13.62	5.79	7.83	3.88	6.03	3.56
	Minnesota	24.01	11.43	7.60	4.31	4.95	3.01
	Montana	19.68	6.46	8.15	3.47	5.35	2.29
	North Dakota	18.31	6.73	8.17	3.80	5.25	2.55
	Oregon	13.09	3.18	5.55	1.72	3.81	1.46
	South Dakota	12.23	8.98	5.59	3.16	4.04	2.05
	Washington	18.93	6.79	8.40	3.69	5.50	2.71
	Total	**17.27**	**7.95**	**7.47**	**3.64**	**5.07**	**2.68**
Winter	California	18.33	4.73	7.57	2.93	5.45	2.16
	Colorado	16.70	8.87	7.11	3.01	4.74	2.09
	Idaho	17.99	7.12	9.78	4.45	6.74	2.73
	Indiana	12.35	6.60	5.80	2.27	4.44	1.95
	Kansas	29.96	15.24	11.22	5.01	7.62	3.68
	Kentucky	17.09	6.32	8.55	4.59	6.12	3.37
	Montana	20.50	6.48	8.81	3.73	6.10	2.55
	Nebraska	18.65	7.07	10.44	5.05	7.63	4.28
	North Dakota	8.05	4.56	4.99	2.78	3.84	2.09
	Oklahoma	30.16	12.02	10.17	5.31	6.09	3.33
	Oregon	18.01	3.30	4.99	2.04	3.38	1.64
	South Dakota	12.63	8.24	6.28	3.72	4.64	2.86
	Texas	38.91	26.58	16.35	12.15	10.17	6.86
	Washington	26.12	11.12	10.64	4.73	6.88	2.77
	Wyoming	11.84	4.86	4.48	1.89	2.93	1.41
	Total	**19.53**	**12.08**	**8.31**	**5.21**	**5.69**	**3.43**

Source: Developed by author.

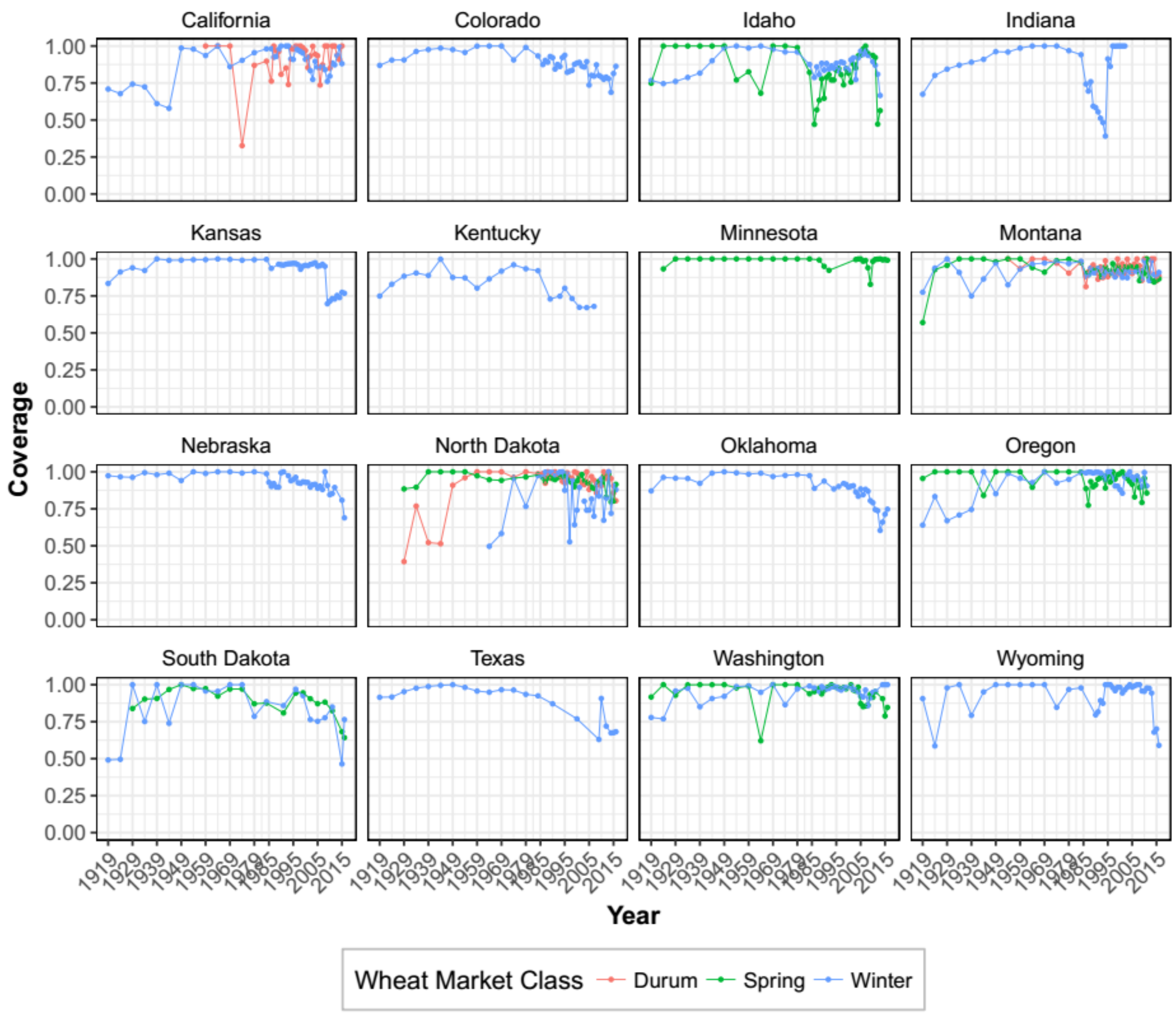

Figure 2-1. Area-by-variety data coverage for major U.S. wheat producing states during 1919-2016.

Source: Developed by author.

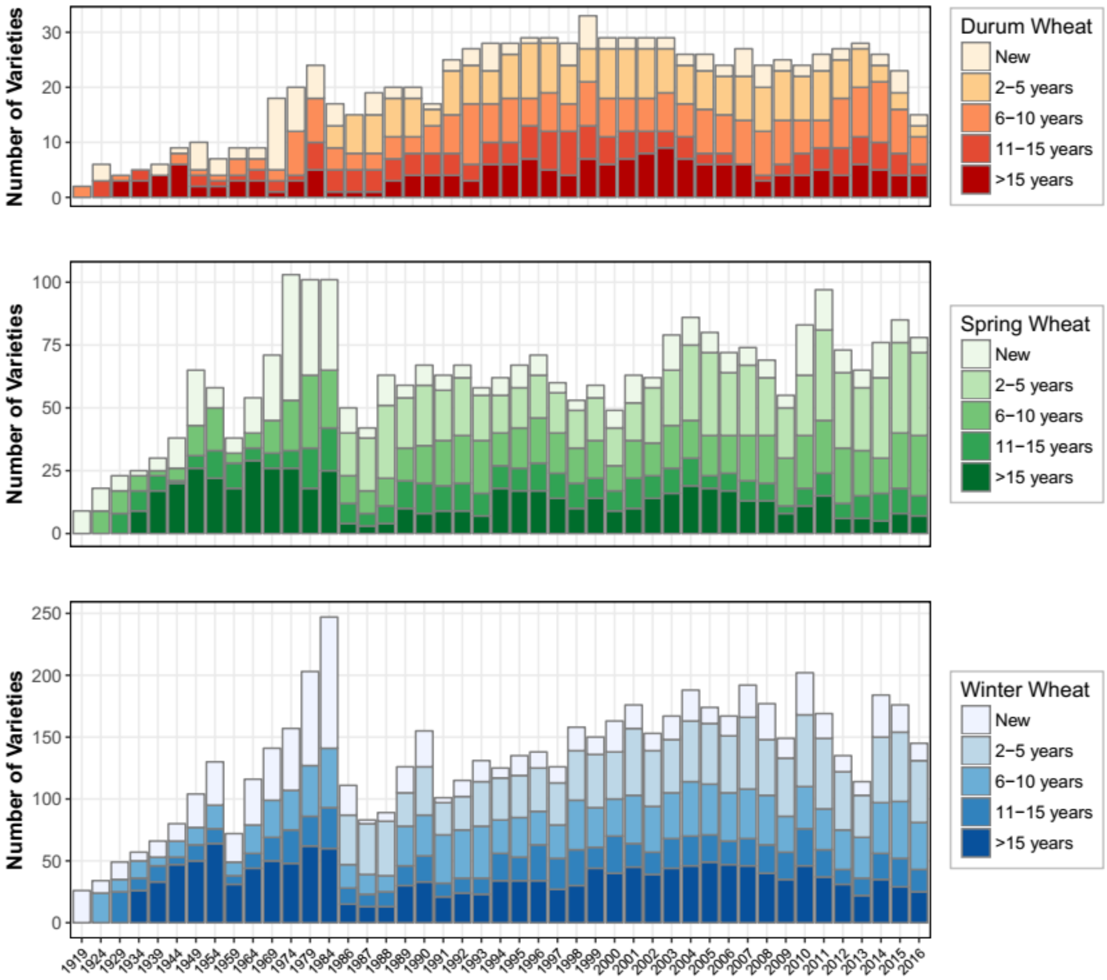

Figure 2-2. Number of wheat varieties planted each year in the U.S., 1919-2016.

Note: The left y-axes are not drawn to the same scale for different wheat market classes.
Source: Developed by author.

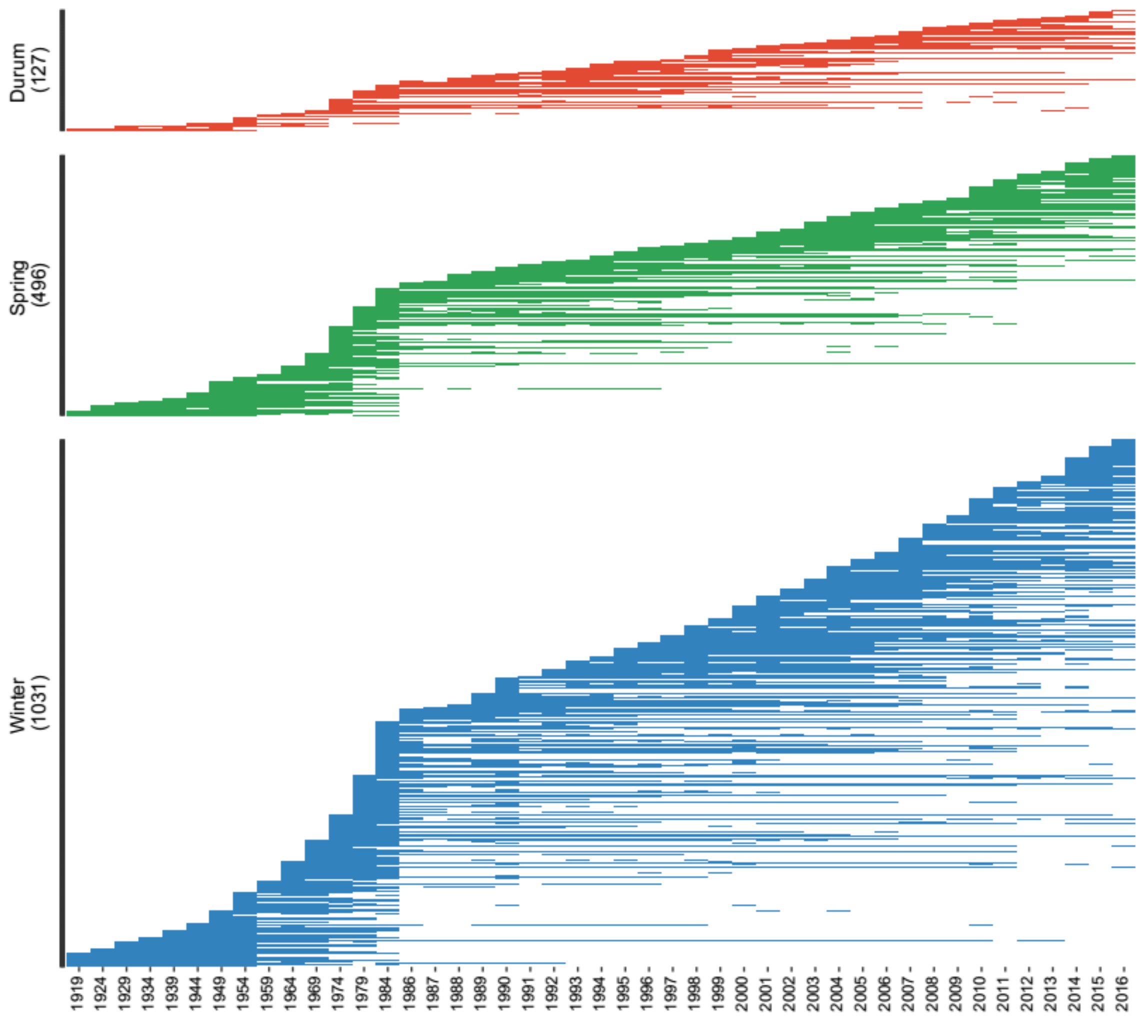

Figure 2-3. Patterns of adoption and discontinuation for wheat varieties in the U.S., 1919-2016.

Note: The y-axes list each unique wheat varieties by the order of their first adoption within different market class. Each colored dash line indicates the presence of a specific variety within each year, where red lines represent durum wheat varieties, green lines represent spring wheat varieties, and blue lines represent winter wheat varieties.
Source: Developed by author.

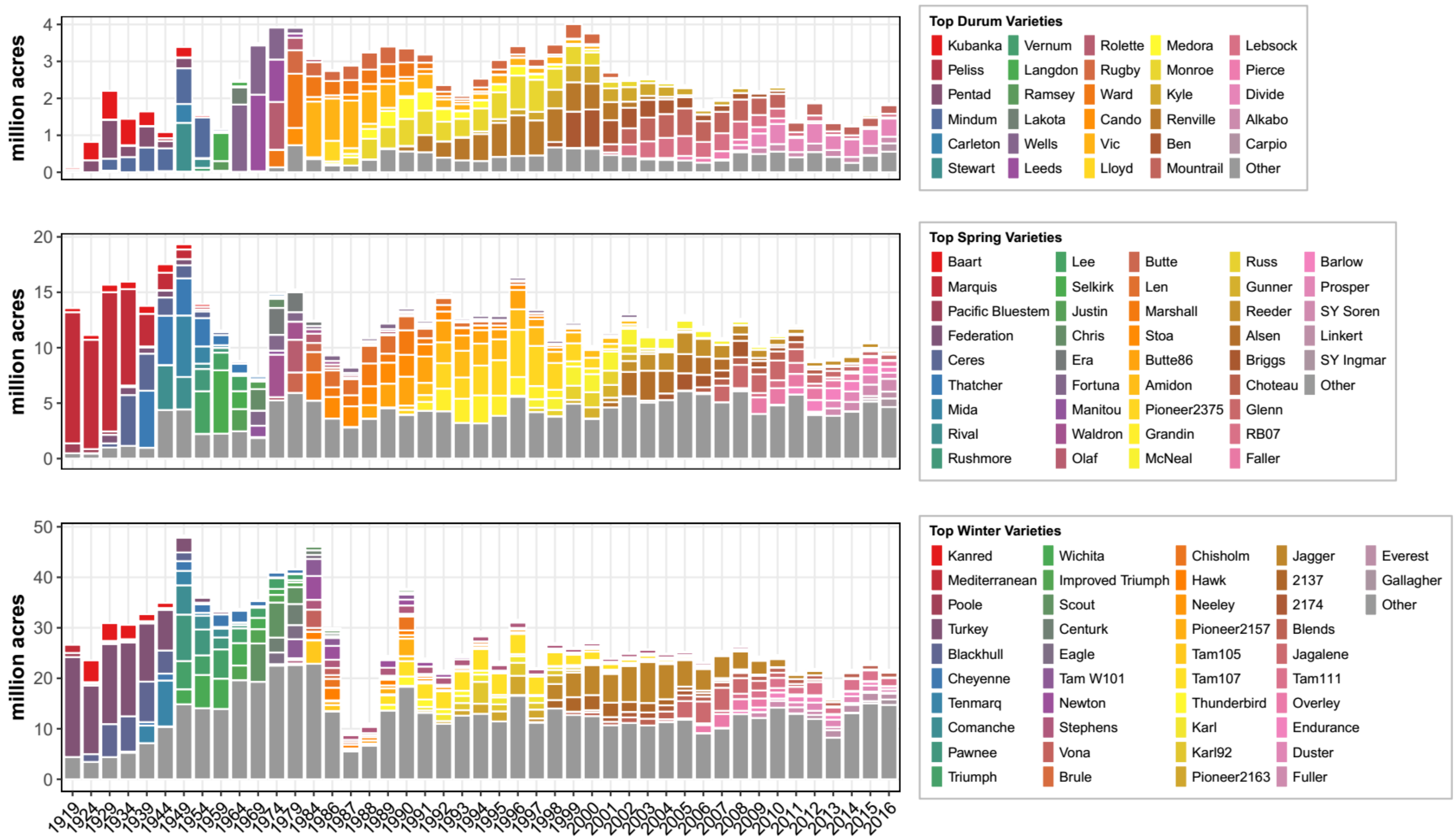

Figure 2-4. Dynamics of planted acreage for top wheat varieties in the United States, 1919-2016.

Note: Top wheat varieties are defined as varieties that have ever been planted as the top three varieties in total area in any given year.
Source: Developed by author.

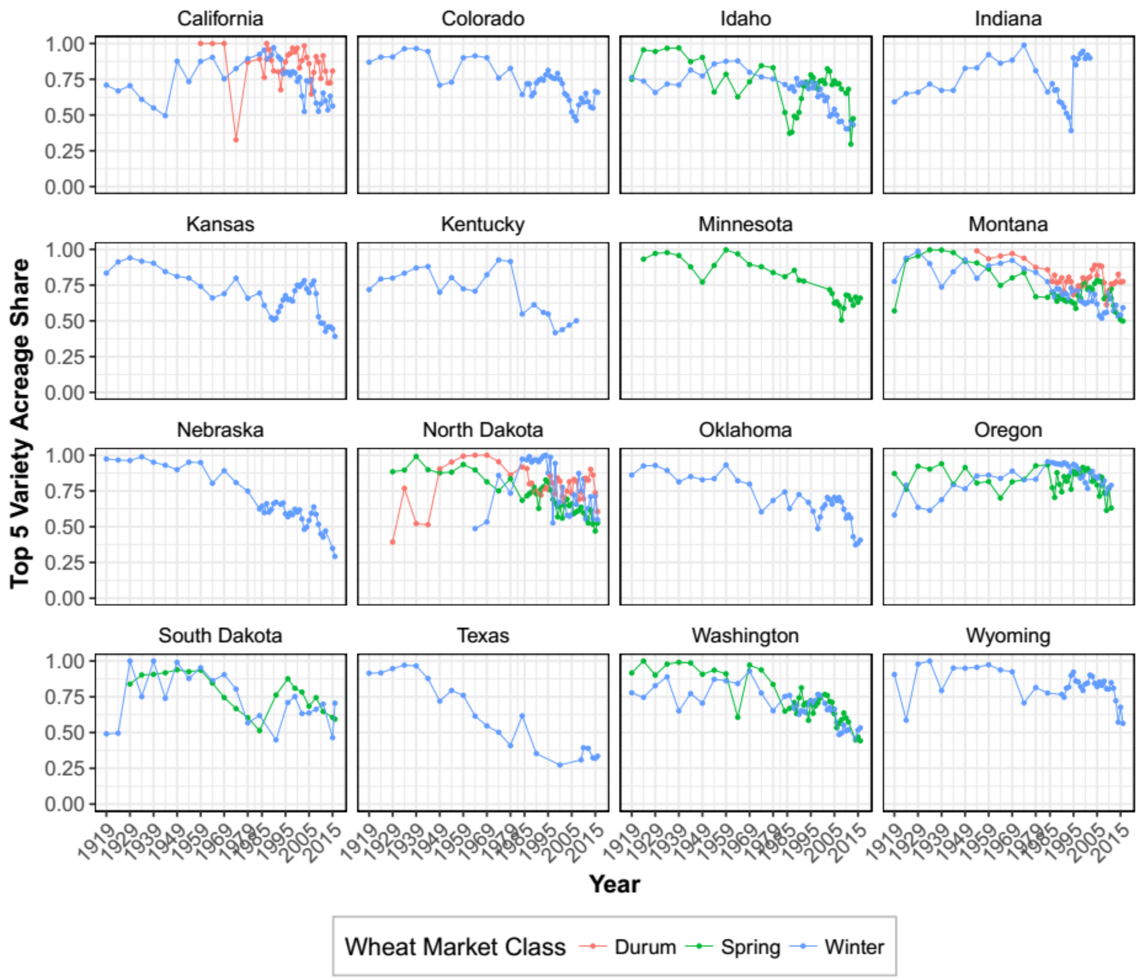

Figure 2-5. Top five variety acreage dominance for major U.S. wheat producing states during 1919-2016.

Source: Developed by author.

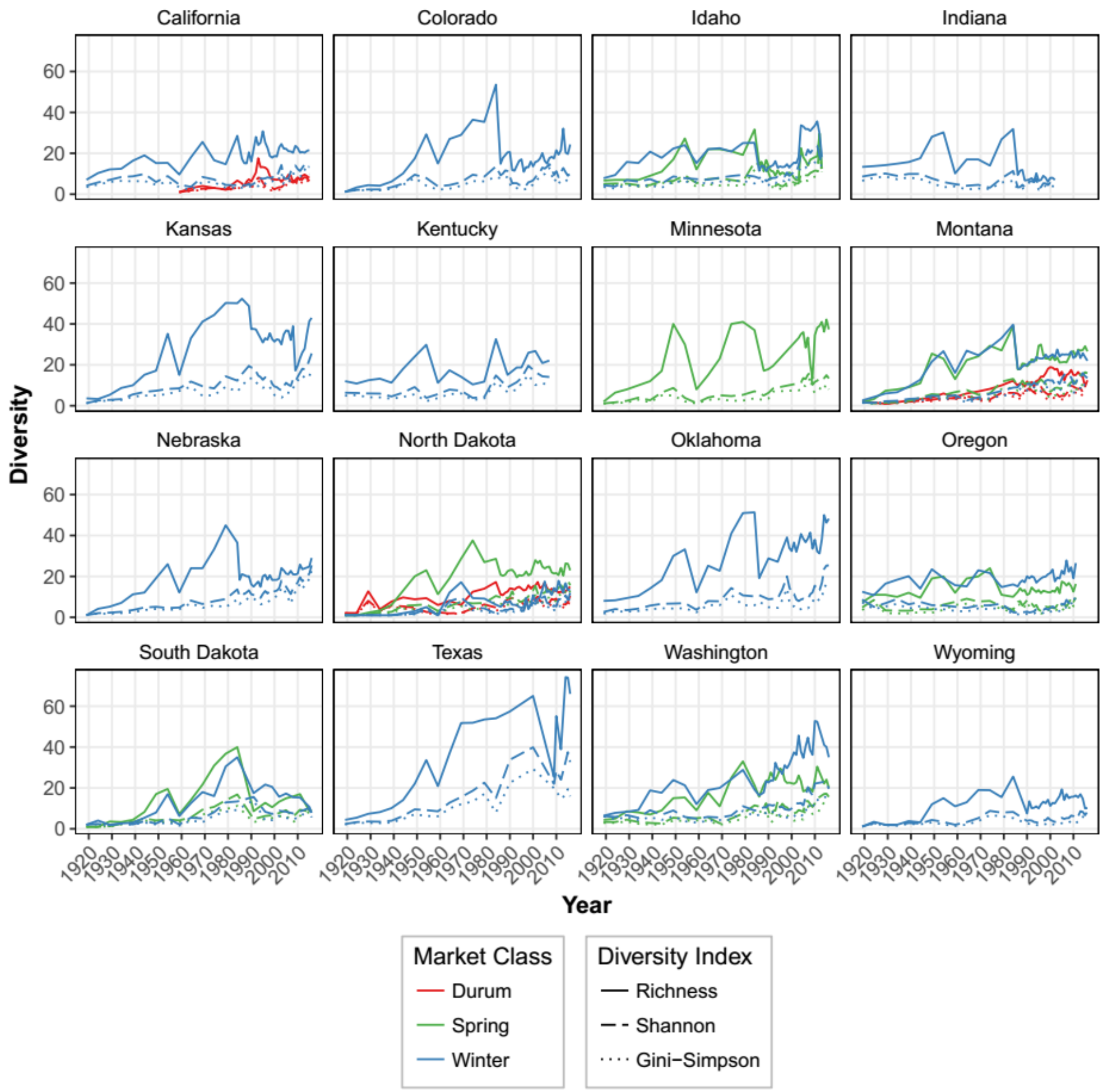

Figure 2-6. Diversity indexes for major U.S. wheat producing states during 1919-2016.

Note: Richness, Shannon and Gini-Simpson indexes are calculated as the HCDT diversity of order 0, 1, and 2, respectively.
Source: Developed by author.

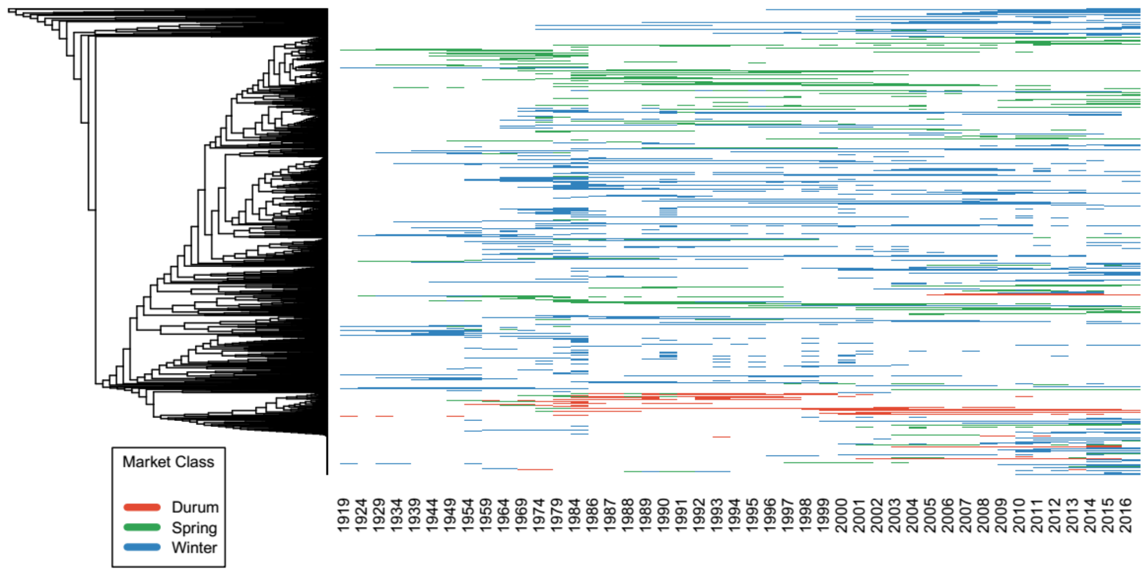

Figure 2-7. Phylogenetic heat map showing the temporal variations for wheat variety genetics in the United States during 1919-2016.

Source: Developed by author.

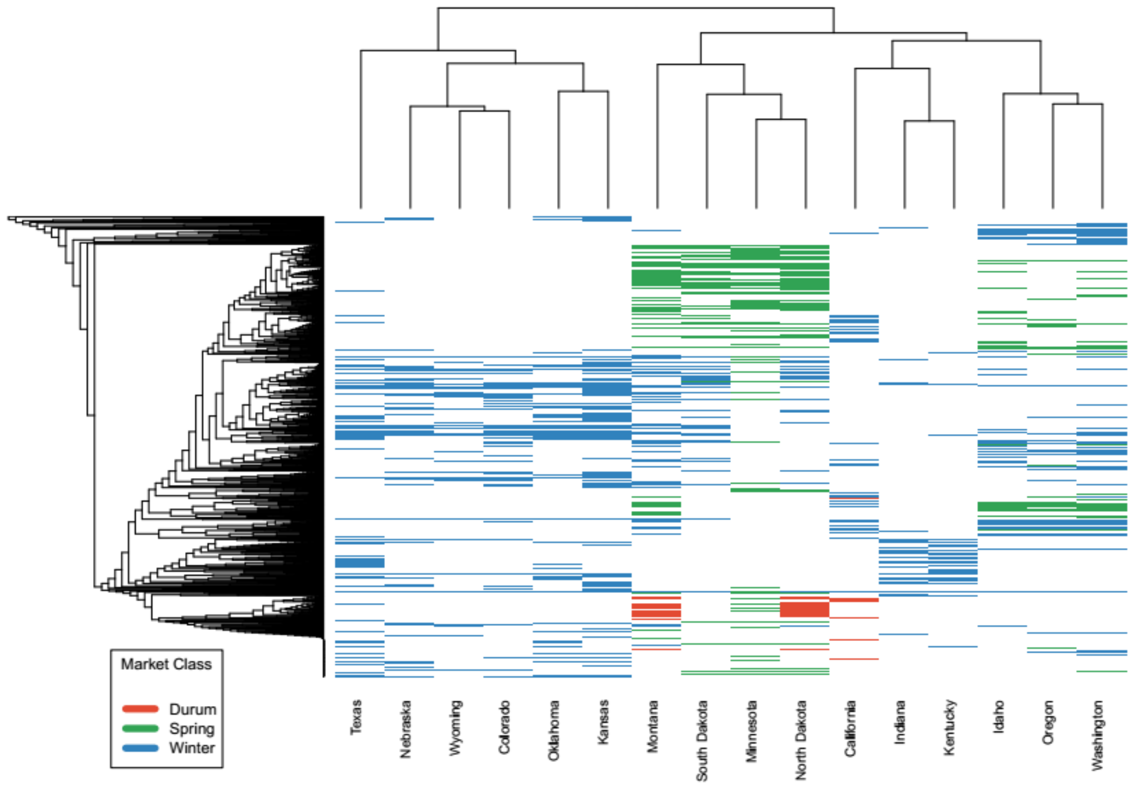

Figure 2-8. Phylogenetic heat map showing the spatial variations for wheat variety genetics in major U.S. wheat growing states during 1919-2016.

Source: Developed by author.

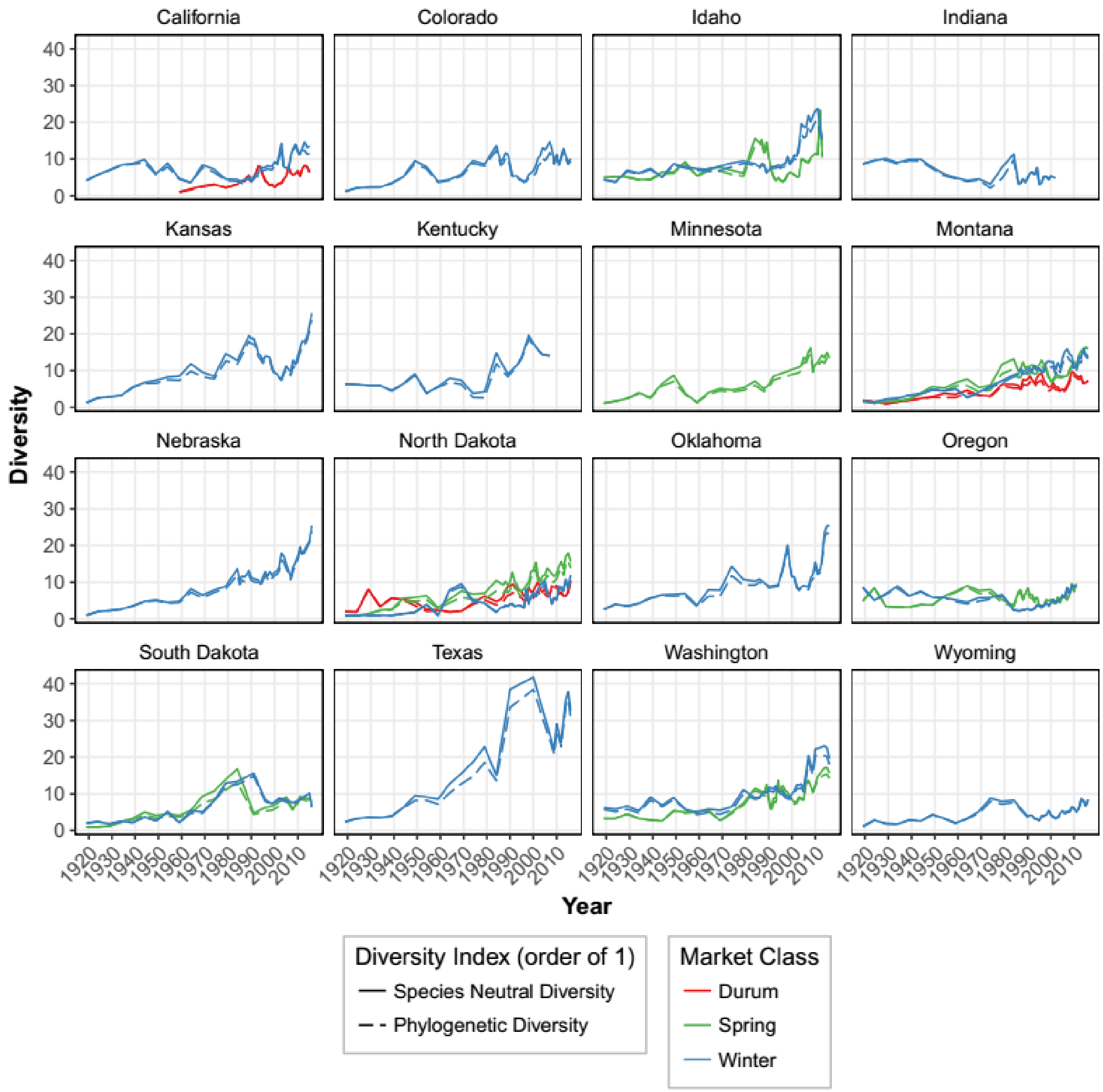

Figure 2-9. Species neutral and phylogenetic diversity indexes of order 1 for major U.S. wheat producing states during 1919-2016.

Source: Developed by author.

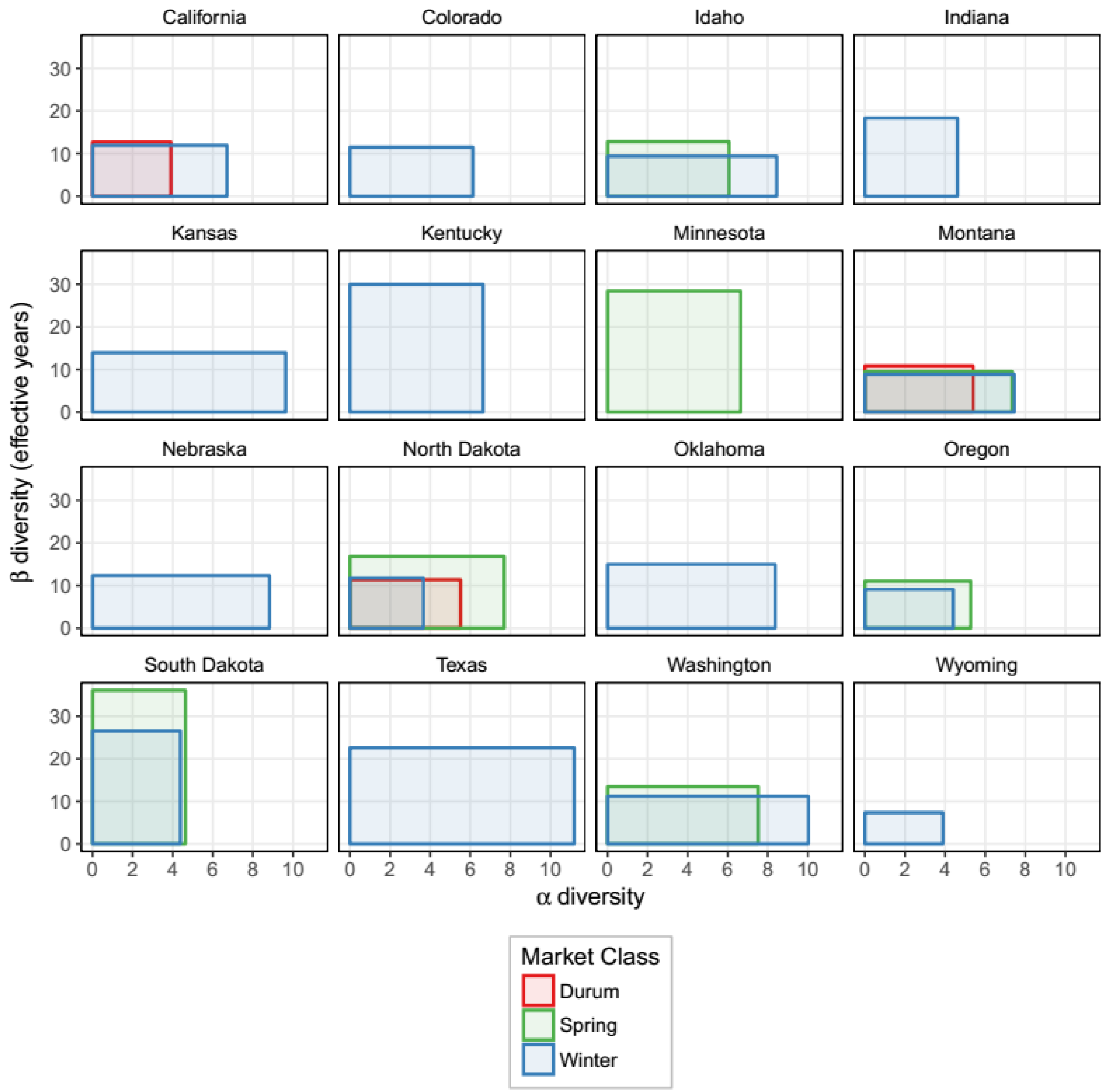

Figure 2-10. Temporal decomposition of phylogenetic diversity for major U.S. wheat producing states during 1919-2016.

Note: x-axis is the average α diversity which represents the average effective number of varieties and y-axis is the β diversity which represents the effective years.
Source: Developed by author.

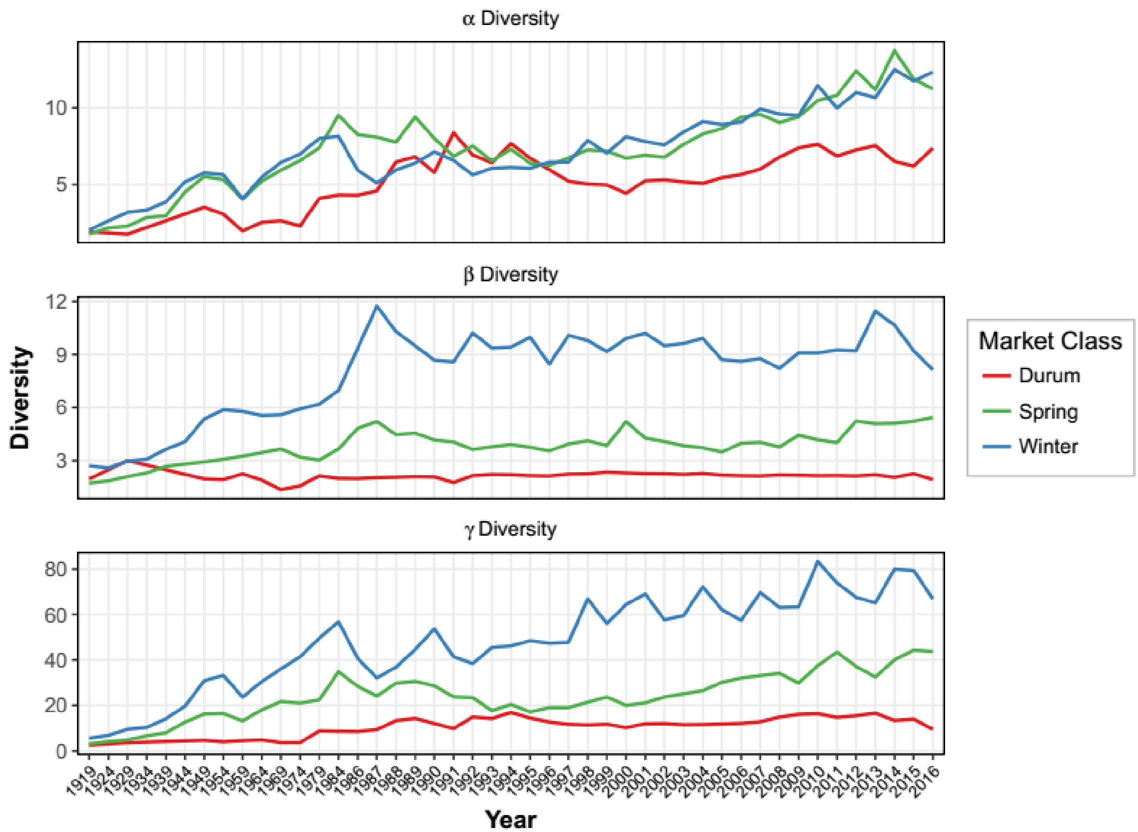

Figure 2-11. Spatial decomposition of phylogenetic diversity for major U.S. wheat producing states during 1919-2016.

Source: Developed by author.

Chapter 3: Effects of Biotic and Abiotic Risks on the Adoption of New Crop Varieties

3.1 Introduction

The choice of crop and crop variety to plant are the first and foremost production decisions faced by farmers. Crop and crop varietal choices not only determine the upfront costs of purchased seed but also the associated costs of fertilizer, pesticide and labor inputs. The Green Revolution is an example of the rapid adoption of modern crop varieties in developing countries where new crop varieties were technically and economically superior to local varieties (Ruttan 1977). Even though many new crop varieties noticeably outperform existing varieties in terms of yield and economic value, adoption processes usually take time so that it is rare to observe immediate and uniform uptake by farmers.

A number of microeconomic theories have been posited to account for the lags in the time pattern of adoption and the incomplete allocation of cropland to new varieties. These include an input and land fixity model (Shumway et al. 1984), a portfolio selection model (Feder 1980), a safety-first model (Hammer 1986), and a learning lag model (Feder and Slade 1984; Lindner et al. 1979). Substantial effort has been invested by scholars in analyzing the determinants of new crop varietal adoption. Feder et al. (1985) provide a thorough review of the empirical work investigating the key explanatory factors affecting adoption. The farm and farmer attributes that are identified as having significant influence include, but are not limited to, farm size, tenure status, farming experience, education level, access to and participation in extension services, access to credit, and provision of crop insurance (Feder et al. 1985; Gamba et al. 2003; Zegeye et al. 2001; Karlan et al. 2014). In addition, environmental factors such as water availability and rainfall conditions also play a significant role in accounting for differences in crop varietal adoption patterns (e.g., David and Otsuka 1990; Upadhyaya et al. 1993). In most cases, adoption behaviors differ across geographical regions, socioeconomic backgrounds and over time. The complex interactions among crop, environment and human mean that the adoption process for each new crop variety varies markedly.

Although agricultural risks play an important role in shaping crop varietal adoption patterns, the empirical evidence on the effects of farmers' exposure to production risks on their varietal choice is limited (Feder et al. 1985; Antle and Crissman 1990). Production risks can stem from either abiotic stresses (e.g., weather, soil or nutrient) or biotic stresses (e.g., weeds, pests and diseases). Many of the desirable traits in new crop varieties relate to the avoidance of the production risks that undermine crop yield. For example, Emerick et al. (2016) demonstrated that a new rice variety with improved flood tolerance had positive effects on farmers' technology adoption behavior in an eastern Indian state. For wheat farmers, one of the most destructive biotic risks are the wheat rust diseases, which cause frequent and substantial yield losses in the United States and worldwide (Chester 1946; Peterson 2001; Kolmer et al. 2007; Huerta-Espino et al. 2011; Wellings 2011; Goyal and Manoharachary 2014). To manage wheat rusts, one of the most common and effective means for farmers is through the deployment of rust resistant varieties. In North America, the deployment of resistant genes and the eradication of the barberry (the alternate host of the stem rust fungus) have been successful in reducing significant losses due to stem rust since the mid-1950s (Kolmer 2005). Globally, the development of stem rust resistant wheat varieties contributed to the Green Revolution beginning in the 1960s, and played an essential role in protecting wheat production by reducing stem rust to negligible levels by the mid-1990s (Singh et al. 2006; Stokstad 2007). However, the deployment of host resistance genes in wheat leads to typical “boom and bust” cycles, where the pathogen population changes rapidly and new rust races emerge to overcome the existing host resistance genes (Eversmeyer and Kramer 2000; Kolmer et al. 2007). Under the constant and ever-evolving threat of wheat rust pathogens, it is beneficial for wheat farmers to replace obsolete susceptible varieties with improved disease-resistant varieties to maintain their yield potential.

Given the important role of both biotic and abiotic risks in the adoption of new varieties, one of the key objectives of this study is to investigate the impact of various agricultural risks on farmers’ crop varietal choices using U.S. wheat as an example. The conceptual framework of this study builds on Lindner et al.'s (1979) learning lag model. Here we extend that model by explicitly incorporating the spatio-temporal dimensions of the agricultural production and risk exposures of farmers into their varietal adoption decisions. For our empirical analysis, we draw on an entirely new compilation of long-term state-level panel data for U.S. wheat to address farmer crop varietal adoption decisions. Past varietal adoption studies typically used either linear regression equations (e.g., Colmenares 1975; Smale, Just and Leathers 1994) or dichotomous choice (e.g., logit, probit or tobit) models (e.g., David and Otsuka 1990; Gamba et al. 2003; Zegeye et al. 2001). In this study we employ a dynamic panel model with explicit spatio-temporal specifications to estimate the effects of farmers’ risk exposure on their crop varietal choice. The differentiation between biotic risks versus abiotic risks and their spatio-temporal dynamics provide novel insights on the role of agricultural risks in shaping farmers' varietal adoption pattern.

3.2 Conceptual Framework

A number of models have been posited to characterize farmers' innovation adoption processes (e.g., Lindner et al. 1979; Feder 1980; Feder and Slade 1984; Shumway et al. 1984; Hammer 1986). This study follows the model proposed by Lindner et al. (1979) and applies it in the context of crop varietal adoption. Specifically, the decision to use a particular crop variety can be conceived as a classical two-action decision problem, where a crop variety A emerges as a potential alternative to replace the current crop variety B. At time period t, the difference in expected profits gained between growing the two varieties can be expressed as:

$$\Pi_{jt}(A) - \Pi_{jt}(B) = C_{jt} \cdot Q_j \tag{3.1}$$

where $\Pi_{jt}(.)$ is the profit derived by farmer j in year t from using new crop variety (A) or current crop variety (B); Q_j measures the scale of production; C_{jt} is a random state variable that measures the difference in average costs between A and B with normal distribution $N(\mu, \sigma^2)$. For a risk-neutral, profit-maximizing farmer, the decision criterion will be

$$\textit{Choose A (adopt crop variety A), if } \mu > 0 \tag{3.2}$$

$$\textit{Choose B (current practice), if } \mu \leq 0 \tag{3.3}$$

The farmer is uncertain about the true value of μ but holds an expectation of μ in year t that is normally distributed with mean Z_t and variance ω_t^2, assuming that the initial expected mean value is $Z_0 < 0$ due to the farmer's ignorance about the productivity of A. Farmer's expectation Z_t is updated after each time period following Bayes Theorem based on the farmer's accumulation of off-farm information regarding C_{jt}, which, in the case of varietal choice, may include yields, sales, prices and other characteristics of variety A reported by off-farm agents such as experimental stations, seed companies, or neighboring farmers. As shown by Lindner et al. (1979), the time to adoption for a farmer can be solved as the minimum value T such that $Z_T > 0$ with the median value of adoption time T^* being:

$$T^* = -\frac{Z_0 \sigma^2}{n \omega_0^2 \mu} \tag{3.4}$$

Equation (3.4) indicates that the optimal adoption time T^* is negatively related to μ (i.e., $\partial T^* / \partial \mu < 0$). The intuition is that the time to adoption will be shorter if the new variety is more profitable compared with the current variety.

Lindner et al.'s (1979) study assumed that the difference in profitability between current and innovative practices for a farmer is fixed (i.e., μ is constant) over time. However, with changes in climate, disease pressure and market conditions, the relative profitability of two crop varieties could also vary over time. For instance, given the co-evolutionary processes at play between a crop and its pathogens, a new crop variety with disease resistance may become relatively more profitable compared with a traditional or prior variety which may be rendered increasingly susceptible if the disease pressure keeps building over time. Similarly, crop varieties with other desirable features, such as drought tolerance, may also become more profitable as the frequency or severity of droughts increase. Thus changes in growing conditions (e.g., climate change, disease epidemics, and so on) can cause the relative profitability of crop varieties to change over time.

To capture the changes in relative profitability over time, the realized value of the average difference between current and new varieties can be conceived as a function of the growing conditions g_t. That is, instead of a time invariant μ, we have $\mu(g_t)$. Assuming growing the new variety generates higher relative benefits compared with current varieties under increasingly more stressful conditions, equation (3.4) indicates that the optimal time to adopt would be shortened. According to this conceptual model, crop variety replacement[1] is driven by the difference in expected profitability of current and new crop varieties, which is a function of the characteristics of different crop varieties, the spatial and temporal variable environmental conditions and the various agricultural risks faced by farmers.

3.3 Empirical Method

An entirely new U.S. state-level panel data set for the period 1989-2016 was compiled for this study, which incorporate varietal adoption patterns, wheat production statistics, and wheat farmers' risk exposures. To track the crop varietal replacement over time, I used an augmented version of the data compiled by the International Science & Technology Practice & Policy (InSTePP) center on the historical pattern of wheat varieties grown in each U.S. state for each of the sampled years throughout the study period (totaling 28 years). To measure the biotic risks associated with wheat rust diseases, I used state-level wheat rust loss data maintained by the USDA Cereal Disease Laboratory (CDL) as an explanatory variable. To measure exposure to other types of risks, I used data on the crop

[1] Opting to use a new variety is a partial or full replacement decision, meaning older varieties are abandoned as new varieties are taken up.

insurance indemnity payments reported by the USDA Risk Management Agency (RMA) since 1989, where the specific causes of yield losses were used to represent the corresponding agricultural risks faced by farmers. Further, wheat production data were obtained from the National Agricultural Statistics Service (NASS) including production, area, yield, and irrigation areas. Both the RMA and NASS data are aggregated to the state level to construct a panel data spanning the period 1989 to 2016. A total of nine major wheat growing states[2] are used for our study because not all wheat growing states in the United States have suitable area-by-variety data.[3] Together, these states represent approximately two thirds of the overall wheat production in the United States based on the 2012 census data reported by NASS.

3.3.1 Measurement of crop varietal replacement

Many prior studies have used binary adoption measures to classify farmers as either "adopters" or "non-adopters" of improved crop varieties. However, these binary measures usually rely on an arbitrarily chosen varietal age to differentiate between "old" versus "new" varieties, and by conception and construction limit farmers' choice to be either 0 for non-adopters or 1 for adopters for each of these varietal types. In reality, farmers may choose a mix of older and newer crop varieties. Moreover, not all farmers use the same crop variety, thus binary varietal adoption models give a highly constrained view of the

[2] The nine included states are California, Colorado, Idaho, Kansas, Montana, Nebraska, North Dakota, Oregon, and Washington.

[3] After 1985, the area-by-variety data are reported by the agricultural statistical service in each state. The nine states included in this study have more complete reports of such data, with at least 23 years of data available during the 28-year period 1989-2016. Wyoming is excluded because it lacked rust loss data in the series maintained by USDA CDL.

complexity of varietal adoption. When assessing varietal adoption processes over large geographical areas, the limitations of a binary adoption variable are magnified when farmers within a region simultaneously grow many different (old and new) crop varieties.

Brennan (1984) proposed an index called the proportion of recent varieties (PRV) that measures the aggregated shares of total areas planted to crop varieties released within an arbitrarily determined number of "recent" years, which is calculated as follows:

$$PRV_{it} = \sum_j q_{itj} \text{ where } q_{itj} = \begin{cases} p_{itj} & \text{if year of release} \geq t - m \\ 0 & \text{if year of release} < t - m \end{cases} \tag{3.5}$$

where p_{itj} is the percentage of total area sown to variety j within state i in year t, and m is the number of years used to define "recent". However, this index is sensitive to the choice of lag years and may suffer from sharp discontinuities when the pace of adoption is reasonably rapid (Brennan and Byerlee 1991).

To overcome these limitations, Brennan and Byerlee (1991) proposed a weighted average age (WAA) index to characterize the rate of varietal replacement based on an area-weighted average age of varieties grown by farmers in a given year. The WAA index is computed as follows:

$$WAA_{it} = \sum_j p_{itj} R_{itj} \tag{3.6}$$

where p_{itj} is the proportion of the area covered by variety j within state i in year t; and R_{itj} is the number of years (at time t) since the release of variety j.

Both PRV and WAA indexes measure the rate of crop varietal replacement, but they capture different aspects of the crop adoption process. PRV is sensitive to changes in the relative shares of "recent" crop variety but fails to differentiate between the age of each variety, while WAA is based on the age of each variety since its release and varies in proportion to the acreage sown to each varietal–age cohort within a given region.

Table 3-1 reports summary statistics for the PRV indices, with both a 3-year and 5-year lag defining the notion of "recent," plus the WAA index. The overall mean for the WAA index is 9.0, indicating that the area-weighted average age for wheat varieties in the United States was 9 years for the period 1989-2016. The PRV index indicates that on average, 36.3 percent of the U.S. wheat acreage was planted to varieties released within the past 5 years, with 19.0 percent of the acreage planted to varieties released 3 years ago or less. Figure 3-1 shows the trend of wheat crop varietal replacements for nine major wheat producing states in the United States, measured using the PRV and WAA indexes. By construction, the PRV5 index is never less than the PRV3 index. Also, the PRV5 index is smoother than PRV3 index, suggesting that the proportion of recently released varieties (i.e., within the past three years) is subject to more fluctuations.

Moreover, the WAA index moves in the opposite direction to the PRV5 and PRV3 indexes (Figure 3-1). The negative correlations between the PRV and WAA indexes is also illustrated in the scatterplots reported in Figure 3-2. Intuitively, the PRV index reflects the share of new varieties while the WAA index reflects the "age" or "oldness" of the entire portfolio of planted varieties; thus a higher share of new varieties results in an overall lower average age of the population. The distributions of these indexes vary marked between states as revealed by the density plots that span the diagonal in Figure 3-2. For the WAA index, the mean age of wheat varieties in different states vary across a large range. The variation revealed by these indexes show that that the pattern of adoption (i.e., the rate of varietal turnover) of new wheat varieties follow different paths for different states.

3.3.2 Measurement of agricultural risks

Influenced by the ever-changing economic and biophysical conditions, farm production faces multiple sources of agricultural risks, including market or price risk, production or yield risk, institutional or regulatory risk, financial risk, and personnel risk. Specifically, due to the biological lag between when many crop production decisions are made and when the final returns are realized, the quantity, quality, and prices of the final outputs are unknown at the beginning of a growing season. For this and other reasons, it is impossible to develop timely and directly comparable measures for all the different sources of agricultural risks, and to accurately determine the impact of various risks on the final output. Many studies have used various measures of temperature, precipitation and soil conditions to represent the various weather-related agricultural stresses (e.g., Mendelsohn et al. 1994; Lobell and Asner 2003; Cavatassi et al. 2011). But the link between weather and crop yield (or production) is neither simple nor often direct, since many factors (such as input use, e.g., irrigation) can alter the relationship between weather and production (Shaw 1964; Beddow et al. 2014).

Rather than rely on a complex compilation of market, weather, policy and farm specific risk data, this study utilizes the U.S. farm crop insurance indemnity payments data to represent the various risks affecting crop production. The U.S. Federal Crop Insurance Corporation (FCIC) offers farmers a portfolio of yield and revenue insurance products to protect farmers against crop losses caused by agricultural catastrophes. Since 1980, when the Federal Crop Insurance Act was signed into law, the multiple-peril crop insurance (MPCI) program has played a prominent role in protecting farmers from crop losses caused by various risks. Crop insurance policies typically indemnify the insured farmers for various production and revenue losses. Crop insurance indemnity data reveal not only the types of risks suffered by farmers each year, but also the actual scale of losses incurred due to each type of risk. Compared with studies using climate data as an approximate measurement of agricultural risks, the realized losses associated with the reported insurance payouts are a more direct and more accurate representation of the relevant risks relevant for this study. In addition to the crop insurance data, I also compiled state-level wheat rust loss data made available by the United States Department of Agriculture Cereal Disease Laboratory (USDA-CDL) since 1918 for major cereal crops, to capture the impact of the most important wheat disease on farmer's crop variety replacement decisions. Table 3-2 reports summary statistics for the percent yield losses experienced by wheat farmers attributed to various categories of agricultural risk. The variable "rust loss" reports the state-level yield loss percentage reported by CDL for all three wheat rust diseases, whereas the variable "other diseases" captures the biotic risks reported in crop insurance indemnities excluding the effect from rust losses. This variable is calculated as the residuals from regressing crop insurance biotic losses on rust losses. Variables for the various abiotic losses are calculated as the indemnity payments for each loss category divided by the total insurance liability, and represents the impact of abiotic risks on wheat production. The data reveal that abiotic risks are the predominant cause of wheat production losses. The largest category of abiotic risk affecting wheat production is drought, with a mean loss ratio of 5.0

percent, while rust diseases have a still sizable, albeit smaller, average yield loss of 2.4 percent.

3.3.3 Econometric estimation

Using WAA and PRV indexes to represent the dependent variable, y_{it}, a dynamic panel model with one period autoregressive and lagged losses from various risks as independent explanatory variables can be specified as:

$$y_{it} = \rho y_{i,t-1} + \boldsymbol{Losses_{i,t-1}\beta_1} + \boldsymbol{X_{it}\beta_2} + \boldsymbol{D_t\beta_3} + \tau_i + \varepsilon_{it} \qquad (3.7)$$

where ρ is the autoregressive coefficient; $\boldsymbol{Losses_{i,t-1}}$ is a vector of lagged explanatory variables measuring the losses attributable from various risks; $\boldsymbol{X_{it}}$ is a vector of wheat production characteristics; $\boldsymbol{D_t}$ is the year dummy variables; the $\boldsymbol{\beta}$'s are the coefficients for the explanatory variables; τ_i is a state specific fixed effect; and ε_{it} is an idiosyncratic error term with $E(\varepsilon_{it}) = 0$. The autoregressive specification was used to reflect the history-dependence of farmers' crop variety choices. It is unlikely that farmers would randomly choose varieties from year to year. Instead, in practice – and in line with the decision theoretical model used to motivate this analysis – they likely rely on their past experience with existing varieties and information regarding new varieties to decide which portfolio of varieties to grow each season. The replacement of old varieties is typically an evolving process rather than a non-serially correlated random event. Inclusion of a one-year lagged autoregressive process captures the effect of the past year's variety portfolio on current year varietal choices. The primary variables of interest are the lagged independent variables $\boldsymbol{Losses_{i,t-1}}$, which represent the magnitude of the various biotic and abiotic risks faced by farmers in state i in the previous year. The year dummy variable $\boldsymbol{D_t}$ is included to capture time fixed effects.

A vector of wheat production characteristics $\boldsymbol{X_{it}}$ includes a harvested acreage variable and a percent area irrigated variable. The harvested acreage variable is included to account for changes in the harvested wheat area between and within states over time, while the inclusion of a variable measuring the irrigated share of wheat production area was used to represent the effect of irrigation on crop varietal replacement. Access to irrigation helps relieve drought stress that could potentially influence farmers' varietal choice. As the motivating theoretical framework describes, farmer's adoption behavior is posited to depend on past experience and information accumulated regarding the performance of the new crop variety. Using lagged variables of past agricultural risks is thus theoretically appropriate for testing the impact of these factors on new crop variety adoption.

If we assume there is no autoregressive effect, such that coefficient $\rho = 0$, equation (3.7) becomes a conventional panel data model with state-level fixed effects. In regression equation (3.7), lagged independent variables satisfy the exogeneity assumption because they are unaffected by current period crop variety choices. One major novelty of using crop insurance indemnity data as a measure of the magnitude of the losses associated with biotic and abiotic risks affecting wheat production, is the direct comparability among various sources of risk because all damages are expressed in value terms. These indemnity payments are the actual compensation paid to farmers towards recovering losses caused by each of the insured risks involved in wheat production.

For the full model, where the autoregressive coefficient $\rho \neq 0$, equation (3.7) implies that $y_{i,t-1}$ is correlated with the unobserved individual-level effect μ_i. As a result, OLS or panel data with fixed effect produces an inconsistent estimator. Following Arellano and Bond (1991), we first difference both sides of the equation to remove the individual effect, which yields:

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \boldsymbol{\Delta Losses_{i,t-1}\beta_1} + \boldsymbol{\Delta X_{it}\beta_2} + \Delta \boldsymbol{D_t\beta_3} + \Delta\varepsilon_{it} \tag{3.8}$$

By construction, $\Delta y_{i,t-1}$ is correlated with the error term $\Delta\varepsilon_{it}$. We opted to use lagged levels of Δy_{it} as instruments for $\Delta y_{i,t-1}$ to estimate a dynamic panel model using generalized method-of-moments (GMM) estimators. Strict exogeneity of the explanatory variables rules out the feedback from the idiosyncratic shock at time t to a regressor at time $s < t$, however for either rust disease losses or abiotic losses, it is likely that the choice of varieties will have an impact on the losses observed, which then implies that it is possible that ε_{it} affects $\boldsymbol{Loss_{it'}}$ for $t' \geq t$. In this case, the regressors can be treated as predetermined, which requires that we only include the losses for time periods that are assumed to be unrelated to $\Delta\varepsilon_{it}$. The full dynamic panel model is estimated using the STATA `xtabond` command which implements the GMM estimator derived by Arellano and Bond (1991). The predetermined regressors were specified as needed using the `pre` options of this command.

In addition to using one-year lagged losses, I also conduct the same set of analysis for equation (3.7) using average three-year lagged losses as explanatory variables. Results from one-year and three-year-average losses were then compared to reveal the effect of either short or longer run risk history on farmers' adoption of new crop varieties.

3.4 Results

The regression results using dependent variables PRV3, PRV5 and WAA are reported in Table 3-3 to Table 3-8. Specifically, Table 3-3, Table 3-5, and Table 3-7 report results using one-year lagged losses from various biotic and abiotic risks as the explanatory variables, while Table 3-4, Table 3-6, and Table 3-8 report results using the average value of each of the past three years' losses as the explanatory variables. In each of the tables, the results from the six different model specifications are reported, including (1) pooled OLS without year dummy, (2) pooled OLS with year dummy, (3) panel data with fixed individual effect but not year fixed effect, (4) panel data with both individual state and year fixed effect, (5) the dynamic panel (DP) model without predetermined regressors, and (6) the DP model with predetermined regressors.

3.4.1 Biotic and abiotic losses

Regarding the effect of biotic losses on crop variety turnover, the regression results show that experiencing rust losses in the previous years is significantly correlated with PRV3, PRV5 and WAA indexes for most of the model specifications (Table 3-3 to Table 3-8). For dependent variable PRV3 and PRV5, the coefficients for lagged rust disease losses are positive, while for the dependent variable WAA the coefficients are negative. Since PRV measures the "newness" of varieties, positive coefficients indicate that higher losses due to rust diseases in previous years are significantly correlated with using a higher proportion of newer crop varieties. In other words, after experiencing rust losses, wheat farmers adopt new crop varieties more rapidly or more extensively (in terms of area), thus resulting in a higher PRV index. On the other hand, the WAA index measures the average "age" of all varieties, such that negative coefficients imply that higher losses caused by rust diseases in prior years are correlated with smaller weighted average age, which also implies a higher proportion of newer varieties. These regression results suggest that experiencing losses from rust diseases is indeed correlated with the subsequent uptake of newer wheat varieties.

In stark contrast, none of the loss measures associated with abiotic stresses indicates any consistently significant coefficients. Moreover, their effects differed depending on the types of abiotic losses, the dependent variables and model specifications. Losses associated with cold growing conditions seem to be insignificant in most of the models, while losses stemming from heat stress are either insignificant or show contradictory signs in different model specifications, indicating that there is no clear correlation between extreme (hot or cold) temperatures and farmers' choice of new crop varieties. Wet and drought losses show up as significant in some model specifications, especially for the results of PRV5 and WAA using three-year averaged losses (Table 3-6 and Table 3-8), suggesting that moisture levels may significantly affect farmers' crop varietal choices. Loss due to price declines show significant negative coefficients for the WAA index, suggesting that a drop in the price of wheat may significantly slow the rate of replacement of older wheat varieties.

3.4.2 Effect of risk history

Comparing the coefficients of the past one year of loss versus an average of the past three years of losses, the regression results suggest that historical losses (three-year average) are a) more likely to be significantly correlated with the adoption of new varieties, and b) the magnitude of the effect (in absolute terms) is larger. One intuitive explanation for the more pronounced effect of longer risk history on adoption may be the uncertainties and risks associated with adopting new crop varieties. After experiencing either biotic or abiotic risks, farmers may choose to wait and observe the production consequences from other adopters, or only experiment with new varieties on smaller acreages in the early stage before they collect enough information regarding the performance of new crop variety to commit to fully adopt. Given farmer's caution in adopting new varieties, experiencing prolonged losses over multiple years would increase the incentive for farmers to switch to new varieties.

3.4.3 Autoregressive effect

For the PRV3 and PRV5 indexes, if farmers choose to grow the same wheat varieties over time, depending on the age of each variety within either a three-year or a five-year window, the PRV index would decline over time as the varieties being excluded from the index age.

For simplicity, if we assume varieties are evenly distributed both in age and acreage, when we compare the proportion of new varieties from time period $t-1$ to time period t, we would have $PRV3_t \approx 0.67 \times\ PRV3_{t-1}$ and $PRV5_t \approx 0.8 \times\ PRV5_{t-1}$. However, the results from the dynamic panel models have autoregressive coefficients of around 0.4 and 0.6 for PRV3 and PRV5 respectively, which, based on two-sided *t*-tests, are significantly different from the hypothetical autoregressive coefficients of 0.67 and 0.8 for evenly distributed varieties, implying that the new varieties are not evenly distributed by age or acreage. The relatively smaller autoregressive coefficients reported here indicate that farmer's adoption of the new varieties are not only based on past history of existing varieties, but are also influenced by other factors such as the risk and production history as revealed in the results.

For the WAA index, if farmers opt not to replace existing wheat crop varieties and the same wheat varieties are grown at the same locations each year, one would expect to see the WAA index increase by 1 each year since all existing wheat varieties are one year older one year later:

$$WAA_t = WAA_{t-1} + 1 \tag{3.9}$$

However, the result from the WAA regressions has an autoregressive coefficient around 0.9 and significantly different from 1 based on two-sided *t*-tests, implying that the lag of WAA index only explains part of the adoption story. Wheat farmers are not growing the same crop varieties year after year, instead, new varieties are being adopted depending on various risk and production factors.

3.5 Conclusion

This study investigates whether or not U.S. farmer's wheat varietal choices are sensitive to their exposure to biotic and abiotic risks. A large number of studies have investigated the determinants of farmers' adoption behaviors and identified various biophysical, geographical, socioeconomic, institutional, and technological factors that are significant at explaining new crop variety adoption patterns. Unlike studies using weather, soil, or climate data to model agricultural risks, a novel approach employed in this study involves the use of the USDA RMA's crop insurance indemnity data to reflect the economic impact resulting from various crop production risks. Besides the comprehensive coverage of various categories of risks, another major advantage of using crop insurance indemnity payoff to measure risks is that this measure directly represent the actual damage incurred by each insured type of risk, which are usually difficult to attribute through the use of weather, soil, climate or a few specific disease records.

Using a panel data of nine major U.S. wheat producing states for the period 1989-2016, this study finds that biotic risk from rust diseases appear to significantly accelerate the rate of uptake of new crop varieties. One possible explanation for the significant correlation between rust disease losses and new crop varietal replacement could be that new crop varieties are usually equipped with improved pests and diseases resistance. Under the evolving pressure of rust diseases, the current resistance genes built into existing crop varieties may become less effective or completely break down. Driven by the natural selection process, once the pest or disease population overcomes the resistance, existing crop varieties would become less profitable. In response to changing pests and diseases, new crop varieties are usually released with advanced genetics to maintain disease resistance. When biotic risks escalate, new crop varieties become more profitable and more desirable compared with existing varieties with less effective resistance, thus (profit maximizing) farmers are incentivized to adopt new varieties under ever-evolving biotic risks.

The findings of this study offer great insights for guiding public and private sector efforts in agricultural R&D to breed for new crop varieties with advanced disease resistance to keep up with the evolving pest and disease populations that threaten agricultural production. In addition, successful breeding efforts on improving abiotic stress resistance such as drought and heat resistance in new crop varieties would also generate substantial benefits since damages caused by abiotic risks are more severe than biotic risks. To cope with agricultural risks, farmers have strong incentives to adopt new varieties that are resistant to various abiotic and biotic stresses to help stabilize agricultural production.

Table 3-1. Summary statistics for dependent variables measuring wheat varietal replacement in the United States during 1989-2016

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
PRV3	overall	0.1896	0.1236	0.0099	0.6000	N = 252
	between		0.0539	0.1039	0.2843	n = 9
	within		0.1126	-0.0478	0.6045	T = 28
PRV5	overall	0.3631	0.1792	0.0352	0.7895	N = 252
	between		0.1054	0.1875	0.5321	n = 9
	within		0.1490	-0.0460	0.7409	T = 28
WAA	overall	9.0351	2.4394	4.8381	17.3247	N = 252
	between		2.0064	6.3431	13.0607	n = 9
	within		1.5357	5.2641	13.2991	T = 28

Note: The summary statistics include a total of nine wheat growing states in the United States as listed in footnote 2.
Source: Developed by author.

Table 3-2. Summary statistics for explanatory variables related to wheat production in the United States during 1989-2016

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**	
Rust loss	overall	0.0242	0.0355	0.0000	0.2500	N =	252
	between		0.0154	0.0087	0.0536	n =	9
	within		0.0324	-0.0294	0.2550	T =	28
Other diseases	overall	0.0015	0.0066	-0.0082	0.0535	N =	252
	between		0.0032	-0.0008	0.0097	n =	9
	within		0.0058	-0.0091	0.0454	T =	28
Cold loss	overall	0.0158	0.0252	0.0000	0.2312	N =	252
	between		0.0090	0.0023	0.0305	n =	9
	within		0.0237	-0.0143	0.2166	T =	28
Heat loss	overall	0.0065	0.0127	0.0000	0.1067	N =	252
	between		0.0052	0.0017	0.0186	n =	9
	within		0.0117	-0.0121	0.0946	T =	28
Wet loss	overall	0.0139	0.0367	0.0000	0.2890	N =	252
	between		0.0213	0.0007	0.0615	n =	9
	within		0.0307	-0.0474	0.2414	T =	28
Dry loss	overall	0.0499	0.0706	0.0000	0.4562	N =	252
	between		0.0245	0.0182	0.0886	n =	9
	within		0.0666	-0.0387	0.4175	T =	28
Price loss	overall	0.0042	0.0209	0.0000	0.1953	N =	252
	between		0.0035	0.0002	0.0096	n =	9
	within		0.0206	-0.0054	0.1911	T =	28
Other loss	overall	0.0199	0.0232	0.0000	0.1361	N =	252
	between		0.0199	0.0023	0.0597	n =	9
	within		0.0136	-0.0329	0.0963	T =	28
Harvest Acres	overall	3.6436	3.3440	0.2170	12.5150	N =	252
	between		3.4709	0.4649	9.4256	n =	9
	within		0.6564	1.1040	7.0290	T =	28
Percent Irrigated	overall	0.2015	0.2552	0.0017	0.8781	N =	252
	between		0.2687	0.0024	0.7989	n =	9
	within		0.0260	0.0670	0.2808	T =	28

Source: Developed by author.

Table 3-3. Regression results using dependent variable PRV3 (Proportion of Recent Varieties, released within 3 years) with 1-year lagged explanatory variables

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) DP	(6) DP
L1.PRV3					0.424***	0.478***
					(0.0602)	(0.0588)
L1.Rust loss	0.619**	0.405	0.568**	0.392	0.283	0.350*
	(0.257)	(0.333)	(0.237)	(0.341)	(0.207)	(0.208)
L1.Other diseases	1.169	1.768	0.785	1.219*	1.188	0.989
	(1.985)	(1.877)	(0.601)	(0.637)	(1.081)	(1.093)
L1.Cold loss	-0.277	-0.446	-0.182	-0.439	-0.241	-0.211
	(0.378)	(0.387)	(0.331)	(0.401)	(0.266)	(0.267)
L1.Heat loss	-0.0246	-0.937	0.486	-0.250	0.0210	-0.109
	(0.686)	(0.600)	(0.940)	(0.835)	(0.549)	(0.548)
L1.Wet loss	0.263	0.323*	-0.122	0.158	-0.0646	-0.00357
	(0.214)	(0.186)	(0.285)	(0.187)	(0.209)	(0.210)
L1.Dry loss	0.125	0.00496	0.165	0.0907	0.0579	0.0982
	(0.117)	(0.103)	(0.146)	(0.114)	(0.0998)	(0.0997)
L1.Price loss	0.156	-0.293	0.124	-0.312	0.0853	0.166
	(0.232)	(0.335)	(0.249)	(0.362)	(0.289)	(0.294)
L1.Other loss	0.895*	0.740*	1.125	0.804	0.899**	0.730
	(0.487)	(0.404)	(0.723)	(0.608)	(0.448)	(0.453)
Harvest Acres	0.00789***	0.00860***	-0.0337	0.00686	-0.0299***	-0.0177*
	(0.00291)	(0.00275)	(0.0200)	(0.0238)	(0.0103)	(0.00967)
Percent Irrigated	0.0387	0.0483	0.129	0.205	0.273	0.206
	(0.0486)	(0.0401)	(0.477)	(0.405)	(0.263)	(0.243)
Constant	0.115***	0.0982**	0.244*	0.0597	0.142**	0.101
	(0.0206)	(0.0473)	(0.115)	(0.159)	(0.0698)	(0.0662)
State Fixed Effect	No	No	Yes	Yes	Diff	Diff
Year Fixed Effect	No	Yes	No	Yes	No	No
Predetermined regressors	--	--	--	--	No	Yes
Observations	243	243	243	243	234	234
R-squared	0.110	0.381	0.092	0.328		

Note: Standard errors in parentheses * p<.10 ** p<.05 *** p<.01
Source: Developed by author.

Table 3-4. Regression results using dependent variable PRV3 (Proportion of Recent Varieties, released within 3 years) with average recent three years lagged explanatory variables

	(1) **OLS**	(2) **OLS**	(3) **FE**	(4) **FE**	(5) **DP**	(6) **DP**
L1.PRV3					0.426***	0.472***
					(0.0612)	(0.0598)
L1~3.Rust loss	0.533	0.352	0.695*	0.287	-0.0886	0.109
	(0.457)	(0.500)	(0.360)	(0.465)	(0.398)	(0.389)
L1~3.Other diseases	0.121	2.137	-0.0417	1.601	1.127	-0.0325
	(2.586)	(2.585)	(1.855)	(1.714)	(1.658)	(1.634)
L1~3.Cold loss	0.367	0.0132	0.791	0.206	0.833	0.773
	(0.574)	(0.625)	(0.839)	(0.752)	(0.512)	(0.495)
L1~3.Heat loss	-1.051	-2.133**	0.0909	-0.863	0.219	-0.127
	(0.756)	(0.873)	(1.360)	(1.055)	(0.804)	(0.777)
L1~3.Wet loss	0.835**	0.591*	-0.213	0.190	-0.131	0.118
	(0.340)	(0.343)	(0.659)	(0.395)	(0.358)	(0.353)
L1~3.Dry loss	0.289	0.111	0.320	0.217	0.104	0.215
	(0.176)	(0.146)	(0.237)	(0.178)	(0.145)	(0.141)
L1~3.Price loss	0.940**	0.178	0.903*	0.115	0.586	0.757
	(0.371)	(0.704)	(0.412)	(0.754)	(0.541)	(0.545)
L1~3.Other loss	0.640	0.545	0.784	0.786	0.384	0.108
	(0.528)	(0.485)	(1.114)	(0.732)	(0.747)	(0.742)
Harvest Acres	0.00620**	0.00731**	-0.0359	0.00437	-0.0323***	-0.0179*
	(0.00306)	(0.00304)	(0.0203)	(0.0251)	(0.0113)	(0.0103)
Percent Irrigated	0.0151	0.0381	0.136	0.252	0.313	0.261
	(0.0481)	(0.0418)	(0.447)	(0.409)	(0.271)	(0.248)
Constant	0.112***	0.102**	0.234*	0.0397	0.140*	0.0856
	(0.0233)	(0.0459)	(0.114)	(0.159)	(0.0762)	(0.0710)
State Fixed Effect	No	No	Yes	Yes	Diff	Diff
Year Fixed Effect	No	Yes	No	Yes	No	No
Predetermined regressors	--	--	--	--	No	Yes
Observations	243	243	243	243	234	234
R-squared	0.127	0.384	0.110	0.323		

Note: Standard errors in parentheses * p<.10 ** p<.05 *** p<.01
Source: Developed by author.

Table 3-5. Regression results using dependent variable PRV5 (Proportion of Recent Varieties, released within 5 years) with 1-year lagged explanatory variables

	(1) OLS	**(2) OLS**	**(3) FE**	**(4) FE**	**(5) DP**	**(6) DP**
L1.PRV5					0.590***	0.655***
					(0.0521)	(0.0482)
L1.Rust loss	0.644**	0.415	0.457	0.360	0.169	0.225
	(0.293)	(0.335)	(0.320)	(0.309)	(0.231)	(0.233)
L1.Other diseases	0.964	2.329	0.272	1.796	0.578	0.197
	(2.301)	(2.188)	(1.120)	(1.024)	(1.217)	(1.232)
L1.Cold loss	0.128	-0.222	0.354	-0.0694	0.136	0.156
	(0.352)	(0.374)	(0.377)	(0.423)	(0.297)	(0.302)
L1.Heat loss	0.424	-0.893	1.559	0.653	1.363**	1.083*
	(0.754)	(0.955)	(1.496)	(1.118)	(0.626)	(0.614)
L1.Wet loss	0.504*	0.429*	-0.166	-0.0889	-0.0534	-0.0425
	(0.271)	(0.239)	(0.285)	(0.202)	(0.236)	(0.237)
L1.Dry loss	0.114	0.0211	0.144	0.147	0.0865	0.138
	(0.152)	(0.147)	(0.145)	(0.101)	(0.111)	(0.112)
L1.Price loss	0.408	-0.727	0.492	-0.399	0.250	0.242
	(0.412)	(0.633)	(0.437)	(0.523)	(0.323)	(0.332)
L1.Other loss	1.637***	1.252***	0.997	0.0674	1.108**	0.967*
	(0.497)	(0.462)	(0.671)	(0.575)	(0.501)	(0.508)
Harvest Acres	0.0192***	0.0196***	-0.0482*	-0.0105	-0.0243**	-0.0144
	(0.00415)	(0.00391)	(0.0249)	(0.0323)	(0.0117)	(0.0110)
Percent Irrigated	0.0898	0.0932*	0.410	0.198	-0.204	0.144
	(0.0659)	(0.0557)	(0.436)	(0.589)	(0.295)	(0.274)
Constant	0.208***	0.235***	0.404**	0.336	0.240***	0.111
	(0.0279)	(0.0713)	(0.120)	(0.229)	(0.0800)	(0.0751)
State Fixed Effect	No	No	Yes	Yes	Diff	Diff
Year Fixed Effect	No	Yes	No	Yes	No	No
Predetermined regressors	--	--	--	--	No	Yes
Observations	243	243	243	243	234	234
R-squared	0.188	0.405	0.103	0.307		

Note: Standard errors in parentheses * p<.10 ** p<.05 *** p<.01
Source: Developed by author.

Table 3-6. Regression results using dependent variable PRV5 (Proportion of Recent Varieties, released within 5 years) with average recent three years lagged explanatory variables

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) DP	(6) DP
L1.PRV5					0.548***	0.623***
					(0.0539)	(0.0491)
L1~3.Rust losses	1.556***	1.675***	1.871**	2.264*	0.923**	1.028**
	(0.530)	(0.478)	(0.777)	(1.035)	(0.429)	(0.427)
L1~3.Other diseases	0.658	4.338	0.174	4.489***	1.501	0.147
	(3.083)	(2.750)	(1.463)	(1.134)	(1.812)	(1.806)
L1~3.Cold loss	0.0821	-0.606	0.934	-0.121	0.0935	0.203
	(0.702)	(0.746)	(0.901)	(1.017)	(0.557)	(0.550)
L1~3.Heat loss	0.124	-1.515	2.130	1.137	2.397**	1.120
	(1.068)	(1.140)	(2.588)	(1.874)	(0.938)	(0.862)
L1~3.Wet loss	1.179***	0.854**	-0.578	-0.154	-0.425	-0.147
	(0.438)	(0.405)	(0.808)	(0.494)	(0.406)	(0.389)
L1~3.Dry loss	0.343*	0.253	0.404	0.669**	0.161	0.293*
	(0.202)	(0.185)	(0.316)	(0.228)	(0.158)	(0.156)
L1~3.Price loss	0.410	-2.167**	0.445	-2.535**	-0.221	-0.165
	(0.647)	(0.994)	(0.852)	(0.903)	(0.589)	(0.603)
L1~3.Other loss	2.105***	1.552***	1.937	0.348	1.532*	1.208
	(0.632)	(0.570)	(1.589)	(1.362)	(0.810)	(0.817)
Harvest Acres	0.0158***	0.0147***	-0.0521*	-0.0122	-0.0298**	-0.0168
	(0.00437)	(0.00437)	(0.0242)	(0.0309)	(0.0125)	(0.0115)
Percent Irrigated	0.0488	0.0407	0.296	-0.107	-0.313	0.0244
	(0.0668)	(0.0571)	(0.354)	(0.466)	(0.294)	(0.274)
Constant	0.183***	0.253***	0.372**	0.346*	0.269***	0.128
	(0.0287)	(0.0716)	(0.113)	(0.172)	(0.0841)	(0.0781)
State Fixed Effect	No	No	Yes	Yes	Diff	Diff
Year Fixed Effect	No	Yes	No	Yes	No	No
Predetermined regressors	--	--	--	--	No	Yes
Observations	243	243	243	243	234	234
R-squared	0.244	0.472	0.171	0.368		

Note: Standard errors in parentheses * p<.10 ** p<.05 *** p<.01
Source: Developed by author.

Table 3-7. Regression results using dependent variable WAA (Weight Average Age) with 1-year lagged explanatory variables

	(1) OLS	**(2) OLS**	**(3) FE**	**(4) FE**	**(5) DP**	**(6) DP**
L1.WAA					0.878***	0.889***
					(0.0309)	(0.0281)
L1.Rust loss	-4.863	-1.716	-3.837	-3.086	-5.000***	-5.168***
	(3.176)	(3.579)	(3.838)	(3.383)	(1.424)	(1.391)
L1.Other diseases	7.518	-3.653	12.56	-1.391	-12.96*	-9.809
	(21.54)	(20.16)	(13.70)	(12.84)	(7.608)	(7.413)
L1.Cold loss	2.055	4.420	0.0528	2.572	4.317**	4.367**
	(4.657)	(4.663)	(4.226)	(3.099)	(1.844)	(1.812)
L1.Heat loss	31.92***	49.32***	11.56	18.73	-4.361	-4.307
	(10.61)	(12.15)	(12.76)	(11.94)	(3.804)	(3.704)
L1.Wet loss	-1.071	-0.995	6.503	5.347	1.803	1.741
	(3.651)	(2.758)	(5.245)	(3.045)	(1.465)	(1.426)
L1.Dry loss	3.349	4.847*	1.961	1.811	0.525	0.191
	(2.822)	(2.706)	(3.774)	(3.862)	(0.690)	(0.674)
L1.Price loss	-6.760	4.563	-8.052	0.914	-6.680***	-6.599***
	(4.263)	(7.361)	(6.336)	(9.053)	(1.985)	(1.986)
L1.Other loss	-34.61***	-31.42***	-12.35	-3.317	-2.862	-1.959
	(6.390)	(6.126)	(7.904)	(8.136)	(3.117)	(3.061)
Harvest Acres	-0.396***	-0.401***	0.391**	0.0558	0.157**	0.0814
	(0.0462)	(0.0427)	(0.127)	(0.201)	(0.0766)	(0.0647)
Percent Irrigated	-1.315	-1.443**	-2.019	-4.440	-0.0494	-1.272
	(0.801)	(0.672)	(5.963)	(9.466)	(1.869)	(1.639)
Constant	11.19***	10.31***	8.125***	9.033**	0.662	1.078**
	(0.390)	(0.698)	(0.992)	(2.789)	(0.519)	(0.485)
State Fixed Effect	No	No	Yes	Yes	Diff	Diff
Year Fixed Effect	No	Yes	No	Yes	N/A	N/A
Predetermined regressors	--	--	--	--	No	Yes
Observations	243	243	243	243	234	234
R-squared	0.427	0.582	0.091	0.352		

Note: Standard errors in parentheses * p<.10 ** p<.05 *** p<.01
Source: Developed by author.

Table 3-8. Regression results using dependent variable WAA (Weight Average Age) with average recent three years lagged explanatory variables

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) DP	(6) DP
L1.WAA					0.855***	0.878***
					(0.0327)	(0.0297)
L1~3.Rust loss	-10.77**	-10.66**	-16.82**	-19.06**	-9.275***	-9.218***
	(5.107)	(4.682)	(6.358)	(7.225)	(2.708)	(2.615)
L1~3.Other diseases	17.62	-12.76	13.64	-32.35	-22.43*	-16.40
	(28.01)	(24.70)	(26.93)	(25.45)	(11.54)	(11.19)
L1~3.Cold loss	3.151	13.81*	-9.306	2.555	3.066	1.353
	(8.143)	(7.492)	(14.34)	(13.39)	(3.636)	(3.396)
L1~3.Heat loss	37.35**	64.36***	2.733	16.64	-23.67***	-20.15***
	(14.96)	(16.00)	(29.73)	(25.96)	(5.713)	(5.357)
L1~3.Wet loss	-5.967	-3.743	17.51	12.88**	5.940**	4.219*
	(4.805)	(3.610)	(11.33)	(5.501)	(2.590)	(2.436)
L1~3.Dry loss	5.162	7.666**	4.148	2.063	1.148	0.395
	(3.414)	(3.091)	(5.998)	(6.370)	(1.010)	(0.969)
L1~3.Price loss	-23.15***	-1.599	-25.48	0.468	-10.99***	-10.68***
	(7.874)	(13.58)	(15.67)	(21.46)	(3.753)	(3.746)
L1~3.Other loss	-47.17***	-42.53***	-19.13	-1.027	-1.360	0.119
	(8.415)	(7.780)	(19.47)	(17.58)	(5.137)	(5.071)
Harvest Acres	-0.395***	-0.384***	0.484**	0.163	0.242***	0.124*
	(0.0484)	(0.0454)	(0.172)	(0.271)	(0.0830)	(0.0699)
Percent Irrigated	-1.474*	-1.477**	-4.071	-4.058	-0.135	-1.667
	(0.819)	(0.685)	(6.538)	(9.157)	(1.908)	(1.690)
Constant	11.57***	9.893***	8.634***	8.616**	0.712	1.271**
	(0.427)	(0.732)	(1.350)	(2.574)	(0.566)	(0.529)
State Fixed Effect	No	No	Yes	Yes	Diff	Diff
Year Fixed Effect	No	Yes	No	Yes	N/A	N/A
Predetermined regressors	--	--	--	--	No	Yes
Observations	243	243	243	243	234	234
R-squared	0.470	0.628	0.168	0.381		

Note: Standard errors in parentheses * p<.10 ** p<.05 *** p<.01
Source: Developed by author.

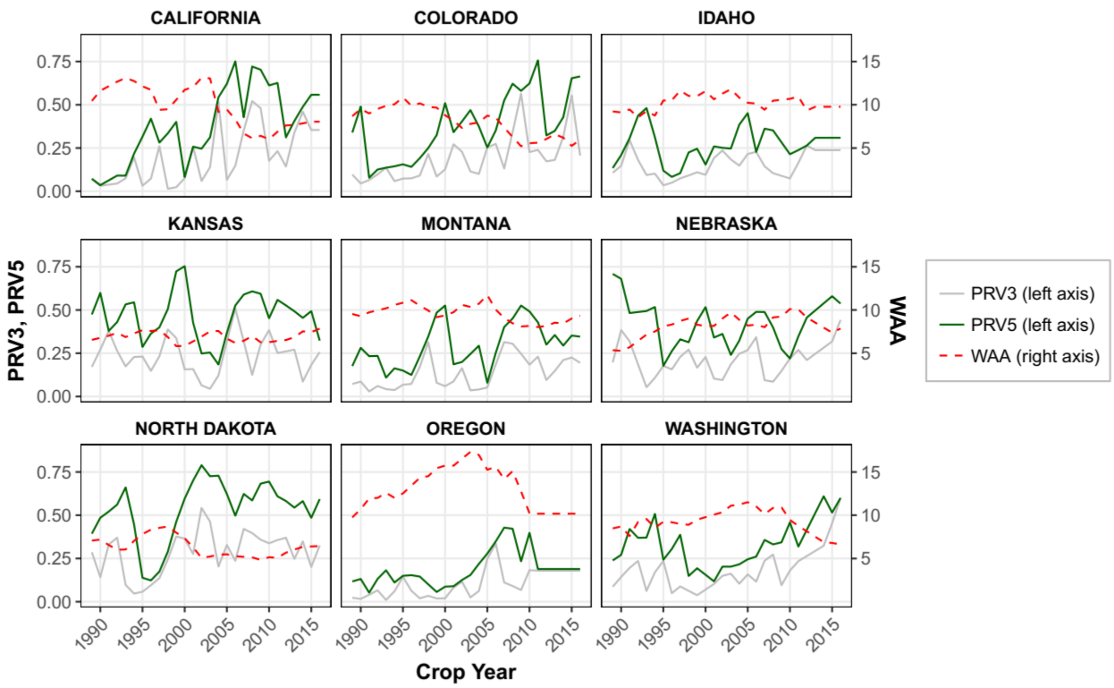

Figure 3-1. Measurements of the wheat crop varietal replacement in 9 wheat producing states of the United States during 1989-2016.

Note: Left axis represent the Proportion of Recent Varieties (PRV) indexes for recent three years (PRV3, grey solid line) and recent five years (PRV5, green solid line). Right axis represents the Weighted Average Age (WAA) index (red dashed line).

Source: Developed by author.

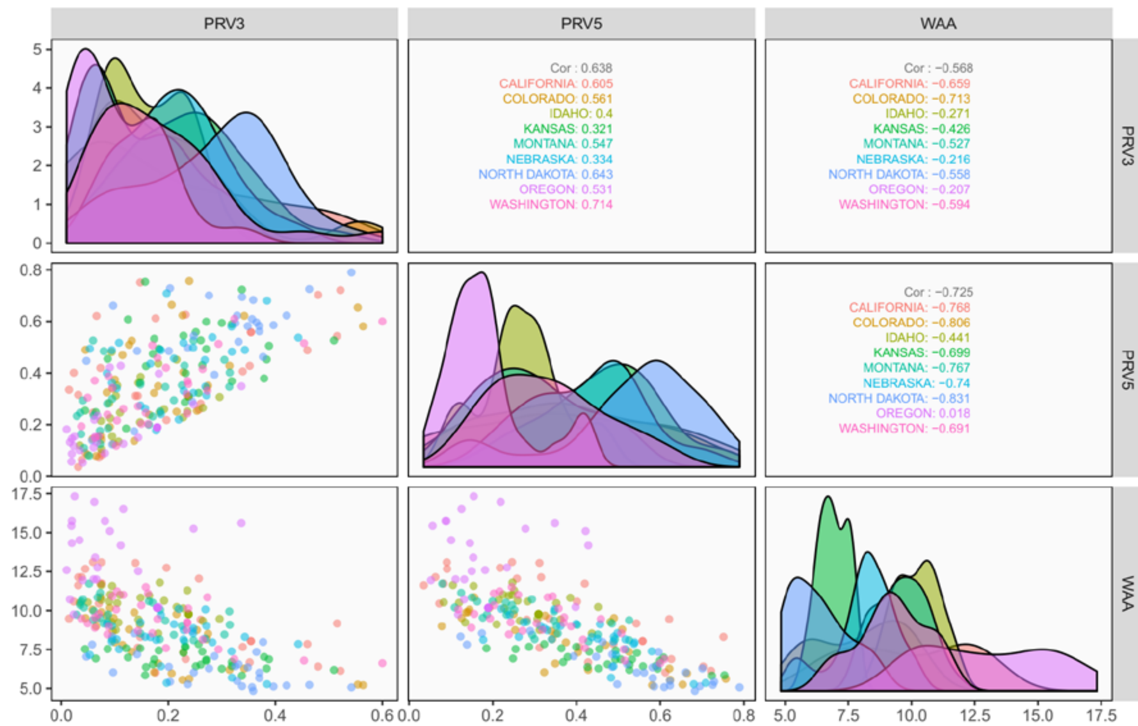

Figure 3-2. Distributions and correlations among the three measurements (PRV3, PRV5 and WAA) of U.S. wheat varietal replacement in 9 wheat producing states.

Note: Upper right cells report the overall and within-state correlation coefficients. Lower left cells are scatter plots between different indexes. Diagonal cells are the density plot for these indexes by state.
Source: Developed by author.

Chapter 4: Risk Types and the Demand for Crop Insurance

4.1 Introduction

Agricultural production is an inherently risky business, with constant but ever-changing exposure to various types of shocks including abiotic risks (such as drought, flood, cold, heat, and soil nutrient deficiency), biotic risks (such as diseases, pests, and weeds), market volatilities (including interest rates, input and output prices), institutional uncertainties (including government policies, crop insurance, and tax laws) and personal risks (including illness, injuries and death). For agricultural production, different types of risks exhibit characteristics distinct from each other in terms of their mode of impact, geographical extent, damage severity, and management strategies. For instance, biotic risks such as pests and diseases usually develop over a period of time and can spread widely across a large geographical extent depending on the specific pathogen, crop hosts and weather patterns. Pests and diseases can potentially be detected early in the season and controlled through chemical applications, management practices, or biotechnological treatments. Abiotic risks, on the other hand, are often more difficult to predict and alleviate. For example, largely unpredictable drought, flooding or hail can lead to severe crop losses. In fact, abiotic risks such as unfavorable environmental conditions are deemed, on average, to pose a much higher threat to crop production than biotic stress (Boyer 1982).

To protect farmers against crop losses caused by various agricultural risks, the U.S. Federal Crop Insurance Corporation (FCIC) offers farmers a portfolio of yield and revenue insurance products for more than 100 crops. Crop insurance can be classified into two types: yield-based coverage and revenue-based coverage, both of which aim to stabilize farmer income. Major yield insurance plans include Actual Production History (APH) and Group Risk Plan (GRP) insurance, based on either individual yield history or county average yield respectively. Major revenue insurance products include Crop Revenue Coverage (CRC), Revenue Assurance (RA), and Income Protection (IP), protecting farmers against lost revenue caused by either low yields, low prices, or both. Since the 1980 Federal Crop Insurance Act was signed into law, the multiple-peril crop insurance (MPCI) program has been playing a prominent role in protecting farmers from crop losses. Indeed, crop insurance has grown markedly during recent decades in the United States, with near three-fold growth in total insured acres and more than 11-fold growth in total premiums paid during 1989-2016 (RMA 2018).[4] However, the provision of crop insurance products is socially costly because of the heavy subsides provided through federal funding, which reached over $6 billion for the crop year 2016 (RMA 2018). Substantive concerns are raised regarding the efficiency, effectiveness, social and environmental viability of relying on crop insurance as the principle agricultural risk management tool (Goodwin and Smith 2013; Smith et al. 2017; Pardey and Smith 2017).

Adverse selection and moral hazard are pervasive concerns regarding the insurance industry, including crop insurance (Quiggin et al. 1993; Knight and Coble 1997; Makki and Somwaru 2001; Glauber 2004). Goodwin (1993) reported that U.S. counties with low loss-risk have considerably more elastic demand for crop insurance than counties with high

---

[4] Total insured acres in the United States were 101 million acres in 1989 and 290 million acres in 2016. Total premiums paid were $814 million in 1989 and $9 billion in 2016.

loss-risk, suggesting that more adversely-selected participants are less responsive to premium increases. Smith and Goodwin (1996) found that the use of crop insurance is associated with a reduction in chemical usage, consistent with the notion that moral hazard behavior may be induced by crop insurance. In addition, Mishra et al. (2005) report that people who purchase revenue insurance tend to spend less on fertilizers. Thus, understanding the factors that influence farmers' decisions to insure their crops is important for creating the proper incentives to increase farmer participation in these program, thereby expanding the risk pool and hopefully reducing the cost of insurance.

Current MPCI contracts do not differentiate among types of risks when determining premium and subsidy levels. The existing literature on farmers' crop insurance decisions usually treat different types of risks equally and examine them as part of an overall bundle of production risks (Ahsan et al. 1982; Nelson and Loehman 1987; Chambers 1989; Goodwin 1993; Smith and Baquet 1996; Makki and Somwaru 2001; Sherrick et al. 2004; Shaik et al. 2008; Adhikari et al. 2013). Past studies show that factors influencing farmers' crop insurance decisions include risk level, premium cost, federal subsidy, expected payoffs, competing risk management options, and farm structural and demographic differences (Goodwin 1993; Smith and Baquet 1996; Makki and Somwaru 2001; Sherrick et al. 2004; Velandia et al. 2009; Enjolras and Sentis 2011; Yu et al. 2018). Adhikari et al. (2013) examined yield guarantee insurance coverage and showed that subsidized yield insurance has substantial benefits for cotton, corn, and wheat farms. Sherrick et al. (2004) found that farmers who are more highly leveraged, less wealthy, riskier, and operate larger acreages engage more extensively in insurance and are more likely to choose revenue protection versus the more specific yield and hail protection.

For crop production, biotic and abiotic risks exhibit different characteristics, thus giving rise to different, and hitherto largely ignored, risk mitigation options for farmers. Both biotic and abiotic risks affect crop production, potentially influencing farmer's purchasing decisions on crop insurance, such as whether or not to buy, the types of crop insurance to buy and levels of coverage to choose. In this paper, I address the question: Do abiotic and biotic risks have differential effects on farmer's demand for crop insurance? To answer this question, I first develop a conceptual framework to characterize farmers' crop insurance decisions under different degrees of biotic and abiotic production risk. In the empirical analysis section, I use the USDA's Risk Management Agency (RMA) county-level wheat production and crop insurance data to examine crop insurance choices made by U.S. wheat farmers subject to different types of production risks. To our knowledge, this is the first attempt to assess the insurance demand implications for farmers facing different types of production risks, where insurance is seen as but one of the options farmers have to mitigate the effects of production risks.

4.2 Conceptual Framework

Assume there are two types of farmers as listed in Table 4-1: Type A faces abiotic production risk with probability α $(0 \leq \alpha \leq 1)$ of having a proportional yield loss L^A $(0 < L^A \leq 1)$; Type B faces biotic production risk with probability β $(0 \leq \beta \leq 1)$ of having a proportional yield loss L^B $(0 < L^B \leq 1)$.

Under the current Multiple Peril Crop Insurance (MPCI) contracts, a U.S. farmer with an average historical yield Y^e under expected market price P^e can choose a yield coverage of θY^e $(0.50 \leq \theta \leq 0.85)$ at a selected guaranteed price δP^e $(0.3 \leq \delta \leq 1)$. In the event of a total crop loss, the insurance liability is $\delta P^e \theta Y^e$. To simplify farmer's choice of insurance contract, I assume that farmers are offered a fixed guaranteed price $\bar{\delta} P^e$ such that the way to adjust insurance coverage is through the yield coverage factor θ. The insurance premium M is determined by the FCIC as a proportion μ of total liability:

$$M = \mu\theta\bar{\delta}P^eY^e \tag{4.1}$$

The government offers a subsidy as a fraction d of the total premium, so the out-of-pocket cost for a farmer purchasing crop insurance is:

$$C^I(\theta) = (1-d)M = (1-d)\mu\theta\bar{\delta}P^eY^e \tag{4.2}$$

Suppose a farmer's potential yield is Y^p when there is no production risk, in state 1, then the actual yield Y_1^a realized under production risk can be expressed as:

$$Y_1^a = Y^p\left(1 - L^{A/B}\right) \tag{4.3}$$

where $L^{A/B}$ represents the proportional loss from abiotic (A) or biotic (B) risks. In state 2 without production risk, the actual yield is the potential yield:

$$Y_2^a = Y^p \tag{4.4}$$

With insurance, the indemnity payment I_s received by the farmer under each state s is given by:

$$I_s(\theta) = max\left\{0, \bar{\delta}P^e(\theta Y^e - Y_s^a)\right\} \tag{4.5}$$

In the short run, when abiotic risks occurred, farmers will not be able to mitigate the losses, either because such losses are unavoidable (such as hail or wind damage) or immediate alleviation strategies are prohibitively expensive (such as drought or flood). In the event of biotic risks, however, farmers have more cost-effective options to reduce losses, for example through pesticide application or other disease management strategies. With an extra input cost C^B, I assume that farmers will be able to reduce the proportional loss due to biotic risk from L^B to $r(C^B)L^B$, where $0 < r(C^B) < 1$ with $r(0) = 1$ and $r(\infty) = 0$. Assume $r' < 0$ and $r'' > 0$ such that higher input costs leads to a greater reduction of biotic losses but with diminishing marginal return.

Assume a farmer's goal is to maximize expected utility of profits across different states. When offered crop insurance products, a farmer chooses an insurance contract θ that maximizes the following expected utility:

$$EU(\theta) = \sum_{s=1}^{2} \phi_s \; U\big(\pi_s(\theta)\big) \tag{4.6}$$

where ϕ_s is the probability that state s occurs, $U(.)$ represents the farmer's utility of profits with the assumption that $U' > 0$ and $U'' < 0$, such that farmers are risk averse and exhibit positive but diminishing marginal utility.

Type A farmer facing abiotic production risk

In state 1, assuming abiotic production risk, the actual yield is lower than the insured yield and the farmer receives a positive amount of indemnity:

$$
\begin{aligned}
\pi_1^A(\theta) &= P^e Y^p (1 - L^A) - C^I(\theta) + I_1(\theta) \\
&= P^e Y^p (1 - L^A) - (1-d)\mu\bar{\delta}\theta P^e Y^e + \bar{\delta} P^e (\theta Y^e - Y_1^a) \\
&= (1-\bar{\delta}) P^e Y^p (1 - L^A) + [1-(1-d)\mu]\bar{\delta}\theta P^e Y^e
\end{aligned} \tag{4.7}
$$

In state 2, because there is no loss, the farmer only pays an insurance premium but receives zero indemnity:

$$
\begin{aligned}
\pi_2^A(\theta) &= P^e Y^p (1-0) - C^I(\theta) + I_2(\theta) \\
&= P^e Y^p - (1-d)\mu\bar{\delta}\theta P^e Y^e + 0 \\
&= P^e Y^p - (1-d)\mu\bar{\delta}\theta P^e Y^e
\end{aligned} \tag{4.8}
$$

From (4.7) and (4.8), for any given choice of insurance coverage, θ, the relationship between profits in the two states is also determined. We have

$$
\begin{aligned}
&\frac{\pi_1^A - (1-\bar{\delta}) P^e Y^p (1-L^A)}{[1-(1-d)\mu]\bar{\delta} P^e Y^e} = \frac{P^e Y^p - \pi_2^A}{(1-d)\mu\bar{\delta} P^e Y^e} \\
\Rightarrow \quad & \pi_1^A(\pi_2^A) = \left[\frac{1-(1-d)\mu}{(1-d)\mu}\right](P^e Y^p - \pi_2^A) + (1-\bar{\delta}) P^e Y^p (1-L^A) \\
\Rightarrow \quad & \pi_1^A(\pi_2^A) = -\left[\frac{1-(1-d)\mu}{(1-d)\mu}\right]\pi_2^A + \left[\frac{1-(1-d)\mu}{(1-d)\mu} + (1-\bar{\delta})(1-L^A)\right] P^e Y^p
\end{aligned} \tag{4.9}
$$

So, for Type A farmers facing abiotic risks and with no alternative risk management options other than to insure the crop, the different choice of insurance coverage, θ, moves the profits in two states along a straight line as determined by equation (4.9). Type A farmer's utility maximization problem can be expressed as:

$$
EU^A(\theta) = \alpha U\big(\pi_1^A(\theta)\big) + (1-\alpha\,) U\big(\pi_2^A(\theta)\big) \tag{4.10}
$$

The first order condition with respect to θ gives:

$$
\begin{aligned}
\alpha U'\big(\pi_1^A(\theta)\big)\left[[1-(1-d)\mu]\bar{\delta} P^e Y^e\right] &= (1-\alpha\,) U'\big(\pi_2^A(\theta)\big)\left[(1-d)\mu\bar{\delta} P^e Y^e\right] \\
\frac{U'\big(\pi_1^A(\theta)\big)}{U'\big(\pi_2^A(\theta)\big)} &= \left(\frac{1-\alpha}{\alpha}\right)\left[\frac{(1-d)\mu}{1-(1-d)\mu}\right]
\end{aligned} \tag{4.11}
$$

So, for Type A farmers facing abiotic production risks, the optimal insurance contract θ^{A^*} is chosen so that the marginal utility from two states satisfies the ratio in equation (4.11). The optimal yield coverage θ^{A^*} is a function of the probability of production risk, the crop insurance premium rate, the subsidy rate, and factors related to the farmer's profits and preferences, including the market price of wheat, farmer's potential yield, and the magnitude of loss under production risk.

Type B farmer facing biotic production risk

With insurance, for Type B farmers facing biotic production risk but able to deploy certain risk management options in addition to insuring the crop, the profits under each state can be expressed as:

$$\begin{aligned} \pi_1^B(C^B,\theta) &= P^eY^p(1-\ r(C^B)L^B) - C^B - C^I(\theta) + I_1(\theta) \\ &= P^eY^p(1-\ r(C^B)L^B) - C^B - (1-d)\mu\bar{\delta}\theta P^eY^e + \bar{\delta}P^e(\theta Y^e - Y_s^a) \\ &= \left(1-\bar{\delta}\right)P^eY^p(1-\ r(C^B)L^B) - C^B + [1-(1-d)\mu]\bar{\delta}\theta P^eY^e \end{aligned} \tag{4.12}$$

and

$$\begin{aligned} \pi_2^B(\theta) &= P^eY^p(1-0) - C^I(\theta) + I_2(\theta) \\ &= P^eY^p - (1-d)\mu\bar{\delta}\theta P^eY^e + 0 \\ &= P^eY^p - (1-d)\mu\bar{\delta}\theta P^eY^e \end{aligned} \tag{4.13}$$

From (4.12) and (4.13), given insurance coverage choice θ, the relationship between profits in the two states is also determined, where

$$\begin{aligned} &\frac{\pi_1^B-\left(1-\bar{\delta}\right)P^eY^p\left(1-r\left(C^B\right)L^B\right)+C^B}{[1-(1-d)\mu]\bar{\delta}P^eY^e} = \frac{P^eY^p-\pi_2^B}{(1-d)\mu\bar{\delta}P^eY^e} \\ \Rightarrow\quad &\pi_1^B(\pi_2^B) = \left[\frac{1-(1-d)\mu}{(1-d)\mu}\right](P^eY^p-\pi_2^B) + \left(1-\bar{\delta}\right)P^eY^p(1-r(C^B)L^B) - C^B \\ \Rightarrow\quad &\pi_1^B(\pi_2^B) = -\left[\frac{1-(1-d)\mu}{(1-d)\mu}\right]\pi_2^B + \left[\frac{1-(1-d)\mu}{(1-d)\mu} + \left(1-\bar{\delta}\right)(1-r(C^B)L^B)\right]P^eY^p - C^B \end{aligned} \tag{4.14}$$

So, once again, a different choice of insurance coverage, θ, moves the profits for Type B farmers facing biotic risks in two states along a straight line as determined by equation (4.14).

Type B farmer's utility maximization problem can be expressed as:

$$EU^B(C^B,\theta) = \beta U\left(\pi_1^B(C^B,\theta)\right) + (1-\beta\,)U\left(\pi_2^B(\theta)\right) \tag{4.15}$$

In state 1, the farmer has an input choice for mitigating biotic risks, where the optimal input choice ${C^B}^*$ satisfies the first order condition from the utility maximization problem (4.15):

$$\begin{aligned} \frac{\partial EU^B(\theta)}{\partial C^B} = \beta U'\left(\pi_1^B(C^B,\theta)\right)\left[-\left(1-\bar{\delta}\right)P^eY^pL^Br'(C^B)-1\right] &= 0 \\ -\left(1-\bar{\delta}\right)P^eY^pL^Br'(C^B) &= 1 \\ r'\left({C^B}^*\right) &= -\frac{1}{(1-\bar{\delta})P^eY^pL^B} \end{aligned} \tag{4.16}$$

Because $r''(.) > 0$, as long as $r'\left({C^B}^*\right) > r'(0)$, we would have ${C^B}^* > 0$. The second order condition guarantees that the optimal ${C^B}^*$ yields a maximum:

$$-\left(1-\bar{\delta}\right)P^eY^pL^Br''\left({C^B}^*\right)\beta U'\left(\pi_1^B\left({C^B}^*,\theta\right)\right) < 0 \tag{4.17}$$

So, the optimal choice of inputs for mitigating biotic risks would be some positive number, indicating that it is better to spend some money on biotic risks control. Specifically, the actual losses $r'\left({C^B}^*\right)L^B$ under state 1 would be lower, so that a Type B farmer will realize larger profits by incurring costs to mitigate the biotic losses than if they opted not to incur these costs:

$$\pi_1^B\left({C^B}^*,\theta\right) \geq \pi_1^B(0,\theta) \tag{4.18}$$

The first order condition of the utility maximization problem (4.15) with respect to θ gives:

$$
\begin{aligned}
\beta U'\left(\pi_1^B\left(C^{B^*},\theta\right)\right)\left[[1-(1-d)\mu]\bar{\delta}P^eY^e\right] &= (1-\beta\,)U'\left(\pi_2^B(\theta)\right)\left[(1-d)\mu\bar{\delta}P^eY^e\right] \\
\frac{U'\left(\pi_1^B\left(C^{B^*},\theta\right)\right)}{U'\left(\pi_2^B(\theta)\right)} &= \left(\frac{1-\beta}{\beta}\right)\left[\frac{(1-d)\mu}{1-(1-d)\mu}\right]
\end{aligned}
\tag{4.19}
$$

So, for a Type B farmer with biotic production risks, the optimal insurance contract θ^{B^*} is chosen so that the marginal utility from two states satisfies the above ratio (4.19), given that the optimal input for mitigating biotic risks C^{B^*} are chosen by the farmer. The optimal yield coverage θ^{B^*} of a Type B farmer is affected by the same factors that affect Type A farmers as mentioned above, but with the addition of the input costs incurred to mitigate biotic risk.

Optimal choice of insurance coverages

To compare the optimal amount of insurance coverage chosen by the two types of farmers, I suppose Type A and Type B farmers face the same probability and level of risks, such that $\alpha = \beta = \phi$ and $L^A = L^B = L$. The choice of insurance coverage levels θ^A and θ^B by the two types of farmers moves the profits in two states along two straight lines (see Figure 4-1) determined by equation (4.9) and equation (4.14) respectively. The two lines are parallel to each other (same slope), with Type B farmer on the right of Type A farmer, according to (4.18) where we have $\pi_1^B\left(C^{B^*},\theta\right) \geq \pi_1^B(0,\theta) = \pi_1^A(\theta)$. Intuitively, farmers facing biotic risks have the option to apply chemical treatment to alleviate biotic risks, thus achieving higher profit under the same insurance coverage level compared with farmers facing abiotic risks. Of note, this conclusion is derived under that assumption that the optimal input use is effective at avoiding production losses and more cost-effective than relying on crop insurance alone.

Now the optimal insurance contract demand for the two types of farmer has the following equality condition:

$$\frac{U'\left(\pi_1^A\left(\theta^{A^*}\right)\right)}{U'\left(\pi_2^A\left(\theta^{A^*}\right)\right)} = \frac{U'\left(\pi_1^B\left(C^{B^*},\theta^{B^*}\right)\right)}{U'\left(\pi_2^B\left(\theta^{B^*}\right)\right)} = \left(\frac{1-\phi}{\phi}\right)\left[\frac{(1-d)\mu}{1-(1-d)\mu}\right] \tag{4.20}$$

This condition states that both Type A and Type B farmers select a coverage level such that the marginal utility from the two states have the same ratio determined by the probability of risks and crop insurance prices. With a diminishing marginal utility function $U''(.) < 0$ and higher profits for type B farmer $\pi_1^B\left(C^{B^*},\theta\right) \geq \pi_1^A(\theta)$ under risks, we must have $U'\left(\pi_1^B\left(C^{B^*},\theta^{B^*}\right)\right) \leq U'\left(\pi_1^A\left(\theta^{A^*}\right)\right)$, which implies that $U'\left(\pi_2^B\left(\theta^{B^*}\right)\right) \leq U'\left(\pi_2^A\left(\theta^{A^*}\right)\right)$ and $\pi_2^B\left(\theta^{B^*}\right) \geq \pi_2^A\left(\theta^{A^*}\right)$ according to equation (4.20). We then have $\theta^{B^*} \leq \theta^{A^*}$, indicating that a type B farmer's optimal choice of insurance coverage is no higher than a type A farmer.

The above results are illustrated in Figure 4-1, where the optimal choices of insurance coverage level for Type A and Type B farmers are different, with the farmer facing biotic risks (Type B) achieves higher profits than Type A farmer facing abiotic risks in both state 1 and state 2. In the state without production risks, the profit for Type A and Type B farmers are determined by their choice of insurance coverage level, θ, according to the same equation. This implies that the optimal choice of insurance coverage for a Type B farmer is smaller than that for a Type A farmer, that is $\theta^{A^*} > \theta^{B^*}$.

The conceptual model indicates that when facing the same probability and levels of losses, Type B farmers facing biotic production risks will select less crop insurance coverage compared with Type A farmers facing unavoidable abiotic production risks. Intuitively, Type B famers have the option of purchasing alternative inputs to mitigate biotic losses, so their optimal insurance coverage is lower since it is more costly to maintain higher levels of insurance coverage if the (marginal) losses can be mitigated through other less costly measures. So how do these postulated differences in the demand for crop insurance stand up to empirical scrutiny?

4.3 Data and Empirical Methods

Based on the conceptual model, maximization of the expected utility of profits implies that a farmer's demand for crop insurance is a function of a farmer's preferences, the distribution of different states of nature, production and marketing activities, and the premium and subsidy of the insurance contracts. In addition, whether the risk is from biotic or abiotic stress could potentially affect the farmer's selection of insurance coverage levels. To empirically assess the consequences of risk types on the demand for crop insurance coverage, I use county-level crop insurance data from the USDA's Risk Management Agency (RMA) and corresponding county-level wheat production data from the USDA's National Agricultural Statistics Service (NASS) for the period 1989 to 2016. A total of 1939 counties from 43 wheat growing states are included in the analysis, which essentially represent all wheat growing counties in the United States (NASS 2018)[5]. Wheat is the second largest indemnified crop after corn in the U.S. However, unlike corn, wheat farmers

[5] Based on NASS survey, the counties included in this study accounts for 97.5 percent of all wheat harvested acres in the United States during the crop year 2016.

do not grow genetically modified varieties for disease control, thus enabling us to analyze the impact of crop insurance as a risk management strategy against biotic and abiotic risks without the potentially confounding aspects of a major biotechnology intervention designed to mitigate one (i.e., biotic) type of risk.

Following Goodwin (1993), I use two separate dependent variables to measure each county's crop insurance demand: (1) the proportion of planted acres actually insured and (2) the liability per planted wheat acre. The proportion of planted acres insured measures the wheat acreage covered by insurance at the county level, regardless of the actual coverage level selection at each insurance unit. This approach ignores different coverage levels farmers may choose on different land. For instance, two counties may have the same proportion of planted acres insured and experience the same amount of yield loss, but they could receive different insurance payments if their yield coverage selections were different.

To reflect the level of insurance coverage, an alternative approach is to use liability per planted acre. Liability is the total indemnities that a farmer would receive in the event of a total loss, determined by the farmer's choice of yield, price, and acreage coverage. Here I use both variables and draw comparisons between them in my analysis.

Using the explanatory variables listed in Table 4-2, I estimate the demand for crop insurance for county i in year t using:

$$\begin{aligned} y_{it} = \alpha_i + \beta_0 + \beta_1 Premium + \beta_2 Subsidy + \beta_3 TotRisk_{t-1} \\ + \beta_4 BioRisk_{t-1} + \beta_5 ShareIrri_t + \beta_6 Yield_{t-1} + \varepsilon_{it} \end{aligned} \tag{4.21}$$

where α_i is a county-specific fixed effect; the β's are the coefficients to be estimated; and ε_{it} is an idiosyncratic error term with $E(\varepsilon_{it}) = 0$.

Insurance premium (*Premium*) is an important price factor affecting farmer's crop insurance purchase decision. Government subsidy (*Subsidy*) affects the actual out-of-pocket costs for farmers, thus directly affecting the demand for crop insurance through reducing the effective insurance premium. The insurance premium and subsidy are divided by the total liability to normalize the measures and enter the analysis as the premium rate and the subsidy rate.

TotalRisk is calculated by dividing total indemnities over total liabilities for each county for a given year, representing the total level of losses experienced by farmers. For *BioRisk*, I use the causes of loss data reported by RMA and aggregate the indemnity claims from biotic causes (i.e., diseases, pests, and weeds), which are then divide by the total indemnity to measure the normalized biotic risk for each county in a given year. An abiotic risk variable was omitted under the assumption that total indemnities not claimed as biotic risk are claimed for abiotic causes. Farmer's total risk and biotic risk are represented using two approaches: the previous one-year's loss ratio and the previous three-years' average loss ratio. The previous one-year's loss ratio represents the immediate history affecting each farmers current crop year insurance decision, assuming that farmers might be short-sighted and the most recent history will have an impact on the current year's insurance decision. The previous three-years' average loss ratio represents the long-term average risk level, thus smoothing insurance implications of an exceptionally high loss year, and reflecting the notion that farmers develop their loss expectations using longer-term averages.

The county production characteristics that influence farmers' choices of crop insurance included in this study are county yield history and the share of irrigated acres. County yield is included as an indicator of the production history of that county. Irrigation is included because farmers could use irrigation to mitigate drought events, thus potentially affecting their demand for crop insurance.

4.4 Results

4.4.1 Spatio-temporal variations of abiotic and biotic risks

Using the indemnity amount as an indicator of production losses reveals that the damages caused by different types of risks vary greatly (Figure 4-2). Overall, abiotic risks are the dominant cause of losses for U.S. wheat farmers, responsible for 97 percent of the total indemnities paid over the entire study period. Drought is the primary cause of loss and accounts for 39 percent of the total indemnities.

Compared with abiotic risks, biotic risks are much less damaging and only account for 3 percent of the total indemnities. Besides the marked differences in the overall damage attributable to abiotic versus biotic risks, these two sources of risk also vary markedly from year to year. Figure 4-3 plots the total indemnities paid for abiotic and biotic risks that affected U.S. wheat farmers each year during the period 1989-2016. The highest total indemnities for abiotic risks occurred in 2013 with more than $2.2 billion paid (equivalent to 15.7 percent of the total crop value of $14.4 billion that year), with more than half that payout attributable just to drought. In that year, biotic risks accounted for $6 million in indemnified losses. The highest indemnity payout for biotic risks occurred in 2014 and 2015 with almost $50 million of loss payouts in both years.

Abiotic and biotic risks also have different geographical extents and spatially variable damage consequences (Figure 4-4). For example, in year 2013, while there were widespread abiotic losses throughout the U.S., wheat growing states within the central plains experienced the most severe losses, whereas during a lower abiotic loss year such as 1994 a few northern states had especially large high indemnity payouts. For biotic risks, during the high losses year 2014, the severe losses were concentrated mainly in the central northern wheat states (e.g., North Dakota, South Dakota and Montana) and the soft red winter wheat region (e.g., Southern Illinois, Indiana and Kentucky), whereas during a lower biotic loss year such as 1992 there were no major losses reported throughout the country. In general, abiotic risks occur over more geographically dispersed areas than biotic risks, although the relative importance of biotic versus abiotic risks in any given location can vary depending on the specific county and the local agroecological and other factors affecting a specific crop year.

4.4.2 Effect of different risks on the demand for crop insurance

Two crop insurance demand equations are estimated using either insured acreage or liability measurements. Depending on whether short-term or long-term risks are used, I estimated a total of four equations using panel data regressions with county-fixed effects. The crop insurance demand equations are estimated in a double-log form and parameter estimates for the two crop insurance demand equations are reported in Table 4-3. In all these equations, the overall F-statistic suggests these models are significant at accounting for variation in the demand for crop insurance.

The regression results indicate that the price elasticity is -2.017 and -1.913 for the two insured acreage proportion equations, and -4.548 and -4.155 for the two liability per planted acre equations using either previous one-year loss ratio or previous three-year average loss ratio as explanatory variables, respectively. The proportion of insured acres is less price elastic than the liability per planted acre in absolute value. Intuitively, liability per planted acre is a more comprehensive measure of insurance coverage whereby farmers can not only vary the number of acres they insure, but they can also adjust the yield or price coverage levels on the acres they opt to insure. Thus it seems likely that changes in the number of insured acres would be less responsive to a change in insurance premium than changes in the liability where the acreage, yield and price aspects of insurance coverage are all reflected. In comparison, the price elasticities reported in prior studies ranged between -0.32 to -0.73 for Iowa corn farmers (Goodwin 1993) and -0.53 to -0.69 for Montana wheat farmers (Smith and Baquet 1996). Due to the differences in data and model specifications, insurance price elasticities from prior studies are not directly comparable with this study. However, the higher price elasticities identify in this study (in absolute value) indicate that, after factoring in the subsidies and different risk types (which are lacking in prior studies), farmers appear to be more sensitive in their choice of crop insurance coverage in response to changes in insurance premium.

As expected, crop insurance subsidies have a positive effect on the demand for crop insurance in both the insured acreage and liability equations, as the subsidies reduce the out-of-pocket costs for farmers. This result is consistent with prior studies on the contribution of premium subsidies on the increased crop insurance participation in the United States (Coble and Barnett 2013; Glauber 2013; Yu et al. 2018). Insured acreage is less elastic in its response to subsidy changes than liability per planted acre, again in line with expectations given that liability encompasses not only a chosen number of acres insured but also yield and price guarantee level selections.

Percent irrigated acres have significant positive coefficients for all equations, which at first seems counterintuitive since irrigation usually stabilizes yield by alleviating losses due to drought, thus reducing the demand for crop insurance as a risk management strategy. Studies have shown that purchasing crop insurance changes farm input use such as fertilizers and pesticides (e.g., Quiggin et al. 1993; Babcock and Hennessy 1996; Smith and Goodwin 1996). Thus irrigation as an agricultural input may have a similar effect on the demand for crop insurance, whereby farmers opt to increase the insurance coverage on these irrigated lands in an effort to "lock in" the returns on these acres to which substantial input costs have been incurred. A recent study by Deryugina and Konar (2017) showed that crop insurance increases irrigation water withdrawals in the United States, consistent with the positive correlation between irrigated acreage share and crop insurance coverage identified in this study.

Preceding year's yield has a significant positive effect on the demand of crop insurance in all equations. This result is inconsistent with Goodwin (1993) findings, where a lower than average yield in the preceding year was found to have a positive effect on insurance purchases for Iowa corn farmers. There are no obvious explanations for such a counter intuitive results. One possible interpretation is that wheat farmers are more willing to purchase insurance to protect high yielding crops, while observing a low yield year would lead the farmers into purchasing less crop insurance because the yield guarantee by crop insurance would be low.

The coefficient of the preceding years' total risk measures the effects of the total risks from preceding years on the current year's crop insurance coverage. All equations have significant positive coefficients, indicating that higher overall risk leads to an increased demand for crop insurance, which again is consistent with the findings of prior studies (Goodwin 1993; Sherrick et al. 2004; Velandia et al. 2009). In all cases, the coefficients of the preceding five years' average risk are greater than the coefficients of the preceding one-year risk for both insured acreage and liability equations, suggesting that farmer's demand for crop insurance is more sensitive to long-term versus shorter-term risk perceptions.

Arguably, the most pertinent finding for this study concerns the effect of biotic risk on the demand for crop insurance. In all specifications, biotic risks have significant negative coefficients. This suggests that holding all other variables constant (especially, total risk exposure), farmers subject to yield loss events associated with biotic risks in the preceding one or three years exhibit a lower demand for crop insurance. This result is in line with the predictions arising from our conceptual model, whereby farmers facing biotic risks will select less crop insurance coverage compared with farmers facing unavoidable abiotic risks. One possible interpretation is that, to cope with biotic risks, wheat farmers can utilize various management strategies other than crop insurance—such as comprehensive disease monitoring, pesticides application, disease resistant varieties adoption, as well as rotation to other crops—to mitigate the consequences of this particular type of risks. Thus, experiencing prior yield losses due to biotic risks does not provide as strong an incentive for the demand for crop insurance as being subject to prior losses associated with abiotic risks.

4.5 Conclusion

The FCIC crop insurance program has grown markedly over the past several decades and become the primary risk management tool for crop farmers in the United States. Many previous studies have investigated the factors influencing farmer's demand for crop insurance, and identified that the loss-risk plays a major role in determining the amount of acreage insured and the choice of yield and price coverage levels. However, to the best of our knowledge, all previous studies on crop insurance demand failed to make the distinction between production losses resulting from different types of risks. Instead, all losses were treated equally in their analysis at either the regional or the farm level. In this study, I argue that biotic risks and abiotic risks are inherently different in the way they impact agricultural production, thus leading to different mitigation strategies. Since crop insurance serves as but one the tools farmers have to hand to mitigate risks in agriculture production, we set out to test the notion that farmers' demand for crop insurance may be sensitive to the type of risk being confronted, given the prospects for the alternatives to insurance to mitigate the various biotic and abiotic sources of risks confronting farmers.

As shown in the theoretical model, farmers facing biotic risks that can be addressed by input options other than insurance (such as chemical pesticides) may opt to purchase less crop insurance coverage compared with farmers facing abiotic risks who lack other risk mitigation options. In other words, biotic risks are likely to have less impact on farmers' demand for crop insurance than abiotic risks. My empirical analysis supports this notion, wherein I show that, following a high loss year, wheat farmers in the U.S., as expected, exhibit an enhanced demand for crop insurance, but this demand increase is not as large if the losses are due to biotic risks compared with abiotic risks.

Differentiating the impacts of different types of risks on farmers' demand for crop insurance has important policy implications, especially for addressing the problems of adverse selection and moral hazard behaviors arising through the provision of crop insurance. Our results highlight the importance of differentiating risk types in the design of crop insurance policies and the delivery of indemnities so as to create the right incentives for farmers to purchase crop insurance products. Without differentiating the types of risks and causes of loss, moral hazard behavior such as poor farm management may lead to increases in the costs of crop insurance for all farmers. In addition, given the difference in crop insurance coverage chosen by farmers facing different risks, the crop insurance premiums can also be adjusted to tailor the specific needs of farmers facing different risk profiles with different risk management practices.

Table 4-1. States of nature for two types of wheat farmers

States of Nature	Probability of Occurrence	
	Type A (Abiotic risk)	**Type B** (Biotic risk)
1 With Losses	α	β
2 No Losses	$(1-\alpha)$	$(1-\beta)$

Source: Developed by author.

Table 4-2 Summary Statistics of Variables Relevant to Crop Insurances Demand for the U.S. Wheat Growing Counties, 1989-2016

Variable	Description	Mean	SD	Min	Max
Dependent variables					
Share of insured acres	Proportion of planted acres insured	0.60	0.29	0.00	1.00
Liability per acre	Real liability per planted acre*	67.50	60.80	0.06	561.68
Explanatory variables					
Premium	Premium cost per dollars of liability	0.14	0.08	0.02	1.17
Subsidy	Subsidy per dollars of liability	0.09	0.06	0.004	0.72
TotRisk	Total indemnities over total liability	0.17	0.20	0.00	1.37
BioRisk	Total indemnities paid for biotic perils over total premium	0.03	0.12	0.00	1.00
ShareIrri	Proportion of acres irrigated	0.24	0.30	0.00	1.00
Yield	County level average wheat yield (bushels/acre)	46.80	17.02	5.00	146.67

Note: * asterisk represents real values are measured in 2000 US dollar.
Source: Developed by author.

Table 4-3. Regression results for U.S. wheat crop insurance demand

	Share of Insured Acres		Liability Per Acre	
	(i)	(ii)	(iii)	(iv)
Premium Rate	-2.017***	-1.913***	-4.548***	-4.155***
	(0.069)	(0.070)	(0.305)	(0.304)
Subsidy Rate	3.740***	3.583***	13.546***	12.549***
	(0.083)	(0.084)	(0.366)	(0.368)
L1. Total Risk	0.085***		0.614***	
	(0.010)		(0.046)	
L1. Share of Biotic Risk	-0.054***		-0.300***	
	(0.015)		(0.068)	
L3. Total Risk		0.114***		1.093***
		(0.015)		(0.066)
L3. Share of Biotic Risk		-0.105***		-0.860***
		(0.023)		(0.099)
Percent irrigated	0.253***	0.243***	0.796***	0.774***
	(0.012)	(0.011)	(0.051)	(0.050)
L1. Yield	0.026***		0.505***	
	(0.006)		(0.028)	
L3. Yield		0.071***		1.033***
		(0.009)		(0.041)
Observations	11091	11376	11091	11376
R^2	0.283	0.278	0.346	0.361
Adjusted R^2	0.233	0.227	0.300	0.316
F Statistics	682.717***	682.604***	915.137***	1,001.963***

Note: Standard error in parenthesis *p<0.1; **p<0.05; ***p<0.01
Source: Developed by author.

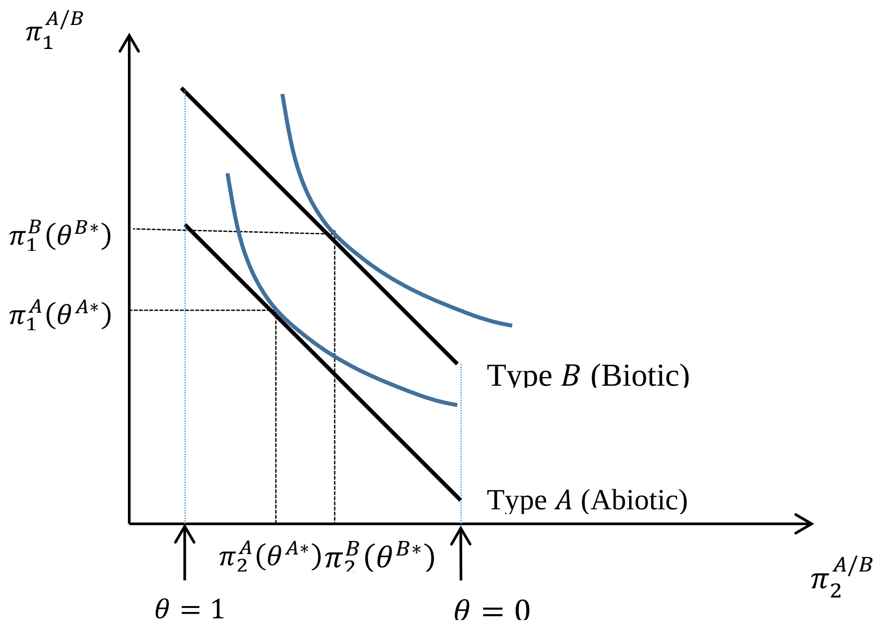

Figure 4-1. Optimal choices of insurance coverage level for Type A (abiotic) and Type B (biotic) farmers.

Source: Developed by author.

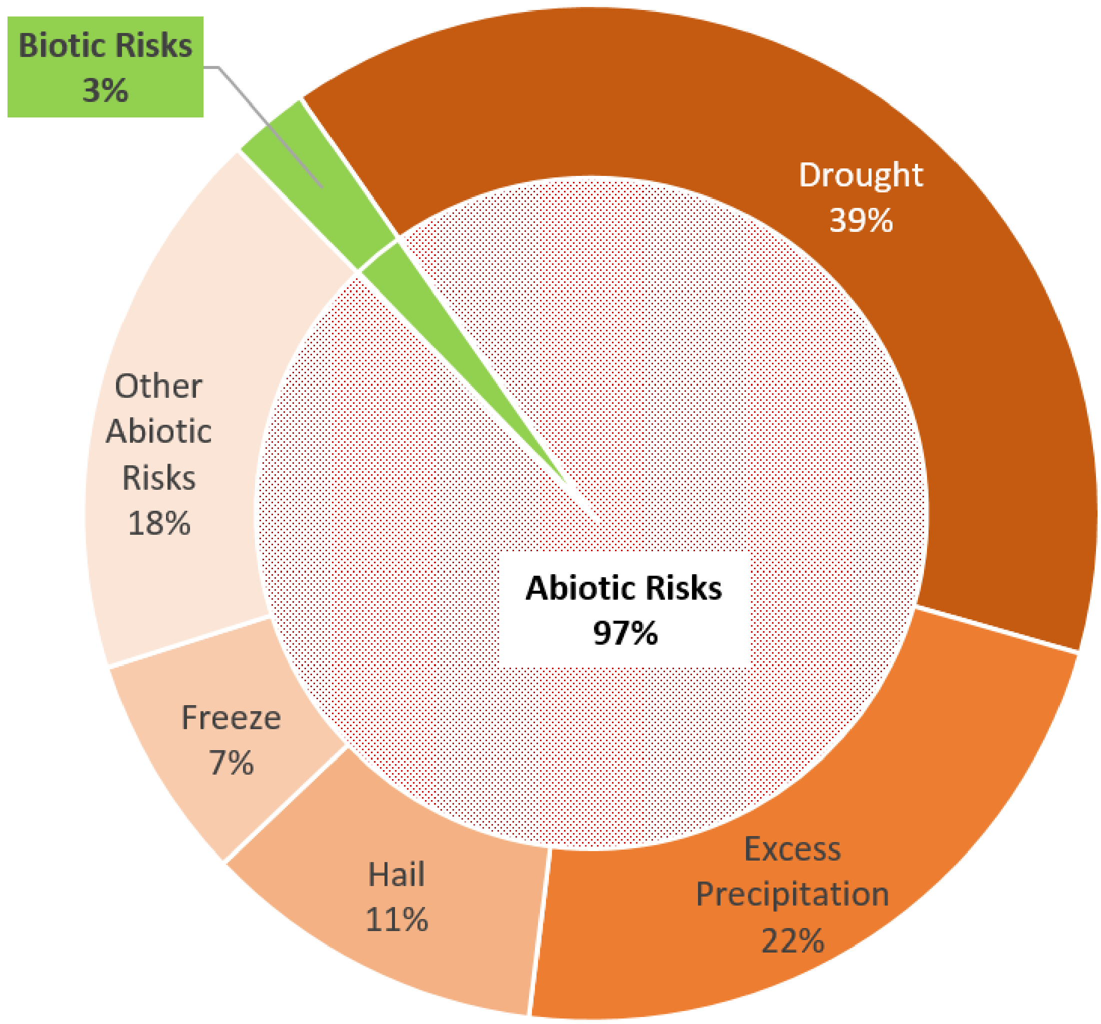

Figure 4-2. Share of total indemnities on U.S. wheat crops by cause of losses, 1989-2016.

Source: Developed by author.

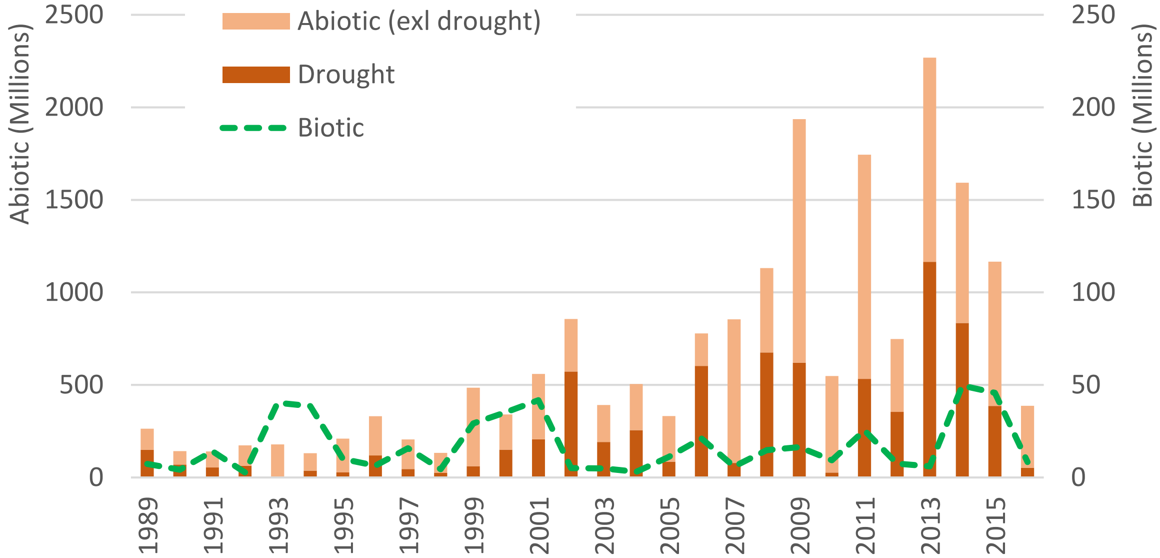

Figure 4-3. Total indemnities paid towards abiotic risks (left axis) and biotic risks (right axis) on U.S. wheat crops annually during 1989-2016.

Source: Developed by author.

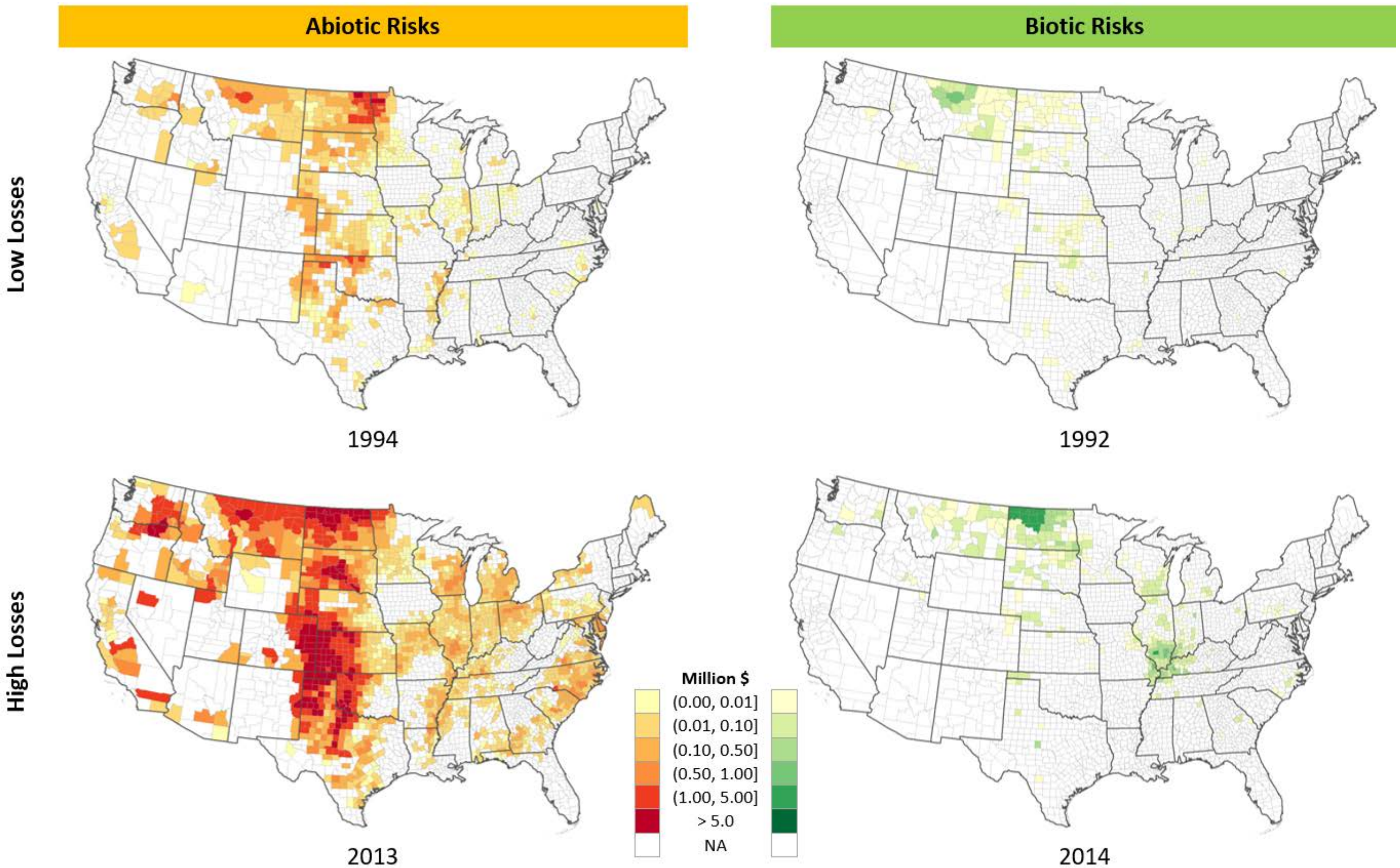

Figure 4-4. Spatial and temporal variations of indemnities on U.S. wheat crops caused by abiotic and biotic risks (selected years illustrating low and high losses).

Source: Developed by author.

Chapter 5: Conclusion

Managing agricultural risks is an extremely challenging task, not least given the vast variability among different risks. The potential damages of different risks depend heavily on the location, time, and environmental factors associated with each specific risk. In response, farmers may implement different *ex ante* and *ex post* strategies to help avoid, reduce or mitigate the impacts of various risks. In this dissertation, I addressed three questions related to agricultural risk management using the example of U.S. wheat production. To do this I 1) measured and analyzed the changing spatio-temporal biodiversity pattern in U.S. wheat varieties over the past century, 2) examined the role of different types of risk on the crop varietal choices of U.S. wheat farmers, and 3) theoretically and empirically examined the impact of different types of risk on U.S. wheat farmers' demand for crop insurance.

Choice of crop varieties is the first and foremost production decision made by a crop farmer, which subsequently determines the accompanying farm management practices (including risk mitigation strategies) needed throughout the entire growing season. Chapter 2 investigates farmers' wheat variety adoption pattern and measures the spatial and temporal biodiversity in U.S. wheat production using detailed, state-level, area-by-variety data since 1919. It is commonly believed that biodiversity is decreasing in modern agriculture. However, the past hundred years' history on U.S. wheat varieties shows that the landscape of modern wheat production actually exhibits increasing agro-biodiversity, both spatially and temporally. The increasing within-species biodiversity is achieved by the breeding efforts of researchers and seed companies in developing new crop varieties that are tailored specifically for the ever-changing biotic and abiotic stresses within different locations. Within a crop species, the increasing number of varieties adopted by farmers enhances agro-biodiversity overall and improves the resilience of modern agriculture against adverse events.

Given the importance of new crop varietal adoption in the context of agricultural risk management, Chapter 3 further explores the different factors that affect farmers' choices of crop varieties, with specific focus on the roles of biotic and abiotic risks. To assess the damages resulting from various agricultural risks, USDA RMA's crop insurance data on indemnity payment by types of risk are used. Insurance indemnities reflect the actual damage suffered by farmers and translates such damages into monetary values, which allows for direct comparison among different sources of risk. Using a panel data of nine major wheat producing states in the U.S. over the period 1989-2016, my study finds that biotic risk from rust diseases is significantly correlated with increasing the rate of adoption of new wheat varieties. Past losses from diseases incentivizes farmers to adopt new varieties with enhanced disease resistance to mitigate future biotic losses. To help farmers cope with risks, crop breeders undertake the important tasks of developing new crop varieties to keep up with the ever-changing production risks.

Crop insurance is also an important *ex ante* risk management tool to help farmers maintain a stable income. Chapter 4 analyzes the difference in farmers' crop insurance demand under different types of risks. Both the theoretical model and empirical analysis show that the impact of biotic risks is smaller than abiotic risks on farmers' demand for crop insurance. One possible explanation is that farmers facing biotic risks have alternative options for pest and disease control other than purchasing crop insurance, such as the application of chemical pesticide or biological control methods. However, farmers facing abiotic risks, such as drought or flood, usually lack options to promptly manage losses caused by such risks during the growing season, which makes crop insurance a more desirable option in coping with abiotic risks. Understanding the impact of different types of risk on farmers' crop insurance demand is helpful for the design of more effective crop insurance policies.

This dissertation deepens our understanding of the impacts of biotic and abiotic risks on agricultural production and the roles of crop variety and crop insurance on risk management. First, this dissertation employs unique panel data that are both spatially and temporally extensive to fully capture the dynamic nature of agricultural production and the associated risks. Furthermore, this dissertation contributes to the existing literature on agricultural risk management by making an explicit distinction between different types of risks based on their unique nature, and the alternative risk management implications of these different types of risk. By so doing, this work helps policymakers understand the dynamic nature of various agricultural risks and helps farmers choose optimal risk management strategies to achieve sustainable production outcomes in the face of disparate types of agricultural risks.

Reference

Adhikari, S., T.O. Knight, and E.J. Belasco. 2013. “Yield Guarantees and the Producer Welfare Benefits of Crop Insurance.” *Journal of Agricultural and Resource Economics* 38(1):78–92.

Ahsan, S.M., A.A. Ali, and N.J. Kurian. 1982. “Toward a theory of agricultural insurance.” *American Journal of Agricultural Economics* 64(3):510–529.

Antle, J.M., and C.C. Crissman. 1990. “Risk, Efficiency, and the Adoption of Modern Crop Varieties: Evidence from the Philippines.” *Economic Development and Cultural Change* 38(3):517–537.

Arellano, M., and S. Bond. 1991. “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.” *The Review of Economic Studies* 58(2):277–297.

Babcock, B.A., and D.A. Hennessy. 1996. “Input Demand under Yield and Revenue Insurance.” *American Journal of Agricultural Economics* 78(2):416–427.

Ball, C.R. 1930. “The History of American Wheat Improvement.” *Agricultural History* 4(2):48–71.

Beddow, J.M., P.G. Pardey, and T.M. Hurley. 2014. “Reassessing the Effects of Weather on Agricultural Productivity.” Available at: http://ageconsearch.umn.edu/handle/172415.

Boyer, J.S. 1982. “Plant productivity and environment.” *Science* 218(4571):443–448.

Brandl, B., and K. Paula. 2014. “The Coordination of Agricultural R&D in the U.S. and Germany: Markets Versus Networks.” In *Modeling, Dynamics, Optimization and Bioeconomics II*. Springer Proceedings in Mathematics & Statistics. Springer, Cham, pp. 75–92. Available at: https://link.springer.com/chapter/10.1007/978-3-319-55236-1_5 [Accessed June 5, 2018].

Brennan, J.P. 1984. “Measuring the Contribution of New Varieties to Increasing Wheat Yields.” *Review of Marketing and Agricultural Economics* 52(3):175–195.

Brennan, J.P., and D. Byerlee. 1991. “The rate of crop varietal replacement on farms: measures and empirical results for wheat.” *Plant Varieties and Seeds* 4(3):99–106.

California Wheat Commission. 2017. "U.S. and California Wheat Classes." Available at: http://www.californiawheat.org/industry/classes-of-us-wheat/ [Accessed November 20, 2017].

Cardinale, B.J., K.L. Matulich, D.U. Hooper, J.E. Byrnes, E. Duffy, L. Gamfeldt, P. Balvanera, M.I. O'Connor, and A. Gonzalez. 2011. "The functional role of producer diversity in ecosystems." *American Journal of Botany* 98(3):572–592.

Cavatassi, R., L. Lipper, and U. Narloch. 2011. "Modern variety adoption and risk management in drought prone areas: insights from the sorghum farmers of eastern Ethiopia." *Agricultural Economics* 42(3):279–292.

Chai, Y., T.M. Hurley, P.G. Pardey, J.M. Beddow, and S.D. Senay. 2018. "A Spatio-Temporal, Multi-Peril Assessment of Wheat Rust Losses Worldwide." *Working paper*.

Chambers, R.G. 1989. "Insurability and moral hazard in agricultural insurance markets." *American Journal of Agricultural Economics* 71(3):604–616.

Chao, A., C.-H. Chiu, and L. Jost. 2010. "Phylogenetic diversity measures based on Hill numbers." *Philosophical Transactions of the Royal Society of London B: Biological Sciences* 365(1558):3599–3609.

Chao, A., C.-H. Chiu, and L. Jost. 2014. "Unifying Species Diversity, Phylogenetic Diversity, Functional Diversity, and Related Similarity and Differentiation Measures Through Hill Numbers." *Annual Review of Ecology, Evolution, and Systematics* 45(1):297–324.

Chester, K.S. 1946. *The nature and prevention of the cereal rusts as exemplified in the leaf rust of wheat.* Waltham: Chronica Botanica.

Chiu, C.-H., and A. Chao. 2014. "Distance-Based Functional Diversity Measures and Their Decomposition: A Framework Based on Hill Numbers." *PLOS ONE* 9(7):e100014.

CIMMYT. 2017. "Genetic Resources Information System for Wheat and Triticale (GRIS)." Available at: http://www.wheatpedigree.net/ [Accessed October 20, 2017].

Coble, K.H., and B.J. Barnett. 2013. "Why Do We Subsidize Crop Insurance?" *American Journal of Agricultural Economics* 95(2):498–504.

Colmenares, J.H. 1975. *Adoption of hybrid seeds and fertilizers among Colombian corn growers*. Mexico: CIMMYT.

Crozier, R.H. 1992. “Genetic diversity and the agony of choice.” *Biological Conservation* 61(1):11–15.

Daróczy, Z. 1970. “Generalized information functions.” *Information and Control* 16(1):36–51.

David, C.C., and K. Otsuka. 1990. “The Modern Seed-fertilizer Technology and Adoption of Labor-saving Technologies: The Philippine Case.” *Australian Journal of Agricultural Economics* 34(2):132–146.

Day-Rubenstein, K.A., P.W. Heisey, R.A. Shoemaker, J. Sullivan, and G.B. Frisvold. 2005. “Crop Genetic Resources: An Economic Appraisal.” Economic Information Bulletion No. 2, United States Department of Agriculture, Economic Research Service.

Deryugina, T., and M. Konar. 2017. “Impacts of crop insurance on water withdrawals for irrigation.” *Advances in Water Resources* 110:437–444.

Donnelly, J. 2002. *Great Irish Potato Famine*. Stroud, UK: The History Press.

Duvick, D.N. 1984. “Genetic diversity in major farm crops on the farm and in reserve.” *Economic Botany* 38(2):161–178.

Emerick, K., A. de Janvry, E. Sadoulet, and M.H. Dar. 2016. “Technological Innovations, Downside Risk, and the Modernization of Agriculture.” *American Economic Review* 106(6):1537–1561.

Enjolras, G., and P. Sentis. 2011. “Crop insurance policies and purchases in France.” *Agricultural Economics* 42(4):475–486.

Eversmeyer, M.G., and C.L. Kramer. 2000. “Epidemiology of Wheat Leaf and Stem Rust in the Central Great Plains of the USA.” *Annual Review of Phytopathology* 38(1):491–513.

Faith, D.P. 1992. “Conservation evaluation and phylogentic diversity.” *Biological Conservation* 61:1–10.

FAO. 2013. “FAOSTAT statistics database: Food Balance Sheets.” Available at: http://www.fao.org/faostat/en/#data/FBS [Accessed June 21, 2017].

Feder, G. 1980. “Farm size, risk aversion and the adoption of new technology under uncertainty.” *Oxford Economic Papers*:263–283.

Feder, G., R.E. Just, and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33(2):255–298.

Feder, G., and R. Slade. 1984. "The Acquisition of Information and the Adoption of New Technology." *American Journal of Agricultural Economics* 66(3):312–320.

Fernandez-Cornejo, J. 2004. "The Seed Industry in U.S. Agriculture: An Exploration of Data and Information on Crop Seed Markets, Regulation, Industry Structure, and Research and Development." No. Agriculture Information Bulletin Number 786, Economic Research Service, USDA.

Fisher, R.A., A.S. Corbet, and C.B. Williams. 1943. "The Relation Between the Number of Species and the Number of Individuals in a Random Sample of an Animal Population." *Journal of Animal Ecology* 12(1):42–58.

Fowler, C. 1994. *Unnatural Selection: Technology, Politics and Plant Evolution*. Switzerland: Gordon and Breach.

Fowler, C., and P.R. Mooney. 1990. *Shattering: food, politics, and the loss of genetic diversity*. Tucson, AZ: University of Arizona Press.

Gamba, P., C. Ngugi, H. Verkuijl, W.M. Mwangi, and F. Kiriswa. 2003. *Wheat farmers' seed management and varietal adoption in Kenya*. Mexico: CIMMYT.

Glauber, J.W. 2004. "Crop insurance reconsidered." *American Journal of Agricultural Economics* 86(5):1179–1195.

Glauber, J.W. 2013. "The growth of the federal crop insurance program, 1990–2011." *American Journal of Agricultural Economics* 95(2):482–488.

Gollin, D. 2006. *Impacts of international research on intertemporal yield stability in wheat and maize: An economic assessment*. Mexico: CIMMYT.

Goodwin, B.K. 1993. "An empirical analysis of the demand for multiple peril crop insurance." *American Journal of Agricultural Economics* 75(2):425–434.

Goodwin, B.K., and V.H. Smith. 2013. "What Harm Is Done By Subsidizing Crop Insurance?" *American Journal of Agricultural Economics* 95(2):489–497.

Goodwin, B.K., M.L. Vandeveer, and J.L. Deal. 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics* 86(4):1058–1077.

Goyal, A., and C. Manoharachary eds. 2014. *Future Challenges in Crop Protection Against Fungal Pathogens*. New York: Springer-Verlag.

Gurr, G.M., S.D. Wratten, and J.M. Luna. 2003. “Multi-function agricultural biodiversity: pest management and other benefits.” *Basic and Applied Ecology* 4(2):107–116.

Hajjar, R., D.I. Jarvis, and B. Gemmill-Herren. 2008. “The utility of crop genetic diversity in maintaining ecosystem services.” *Agriculture, Ecosystems & Environment* 123(4):261–270.

Hammer, J.S. 1986. “‘Subsistence first’: farm allocation decisions in Senegal.” *Journal of Development Economics* 23(2):355–369.

Harwood, J.L., R. Heifner, K. Coble, J. Perry, and A. Somwaru. 1999. *Managing Risk in Farming: Concepts, Research, and Analysis*. Market and Trade Economics Division and Resource Economics Division, Economic Research Service, U.S. Department of Agriculture.

Havrda, J., and F. Charvát. 1967. “Quantification method of classification processes. Concept of structural a-entropy.” *Kybernetika* 3(1):30–35.

Hill, M.O. 1973. “Diversity and Evenness: A Unifying Notation and Its Consequences.” *Ecology* 54(2):427–432.

Huerta-Espino, J., R. Singh, S. Germán, B. McCallum, R. Park, W. Chen, S. Bhardwaj, and H. Goyeau. 2011. “Global status of wheat leaf rust caused by Puccinia triticina.” *Euphytica* 179(1):143–160.

Jost, L. 2006. “Entropy and diversity.” *Oikos* 113(2):363–375.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. “Agricultural Decisions after Relaxing Credit and Risk Constraints.” *The Quarterly Journal of Economics* 129(2):597–652.

Keneni, G., E. Bekele, M. Imtiaz, K. Dagne, G. Keneni, E. Bekele, M. Imtiaz, and K. Dagne. 2012. “Genetic Vulnerability of Modern Crop Cultivars: Causes, Mechanism and Remedies.” *International Journal of Plant Research* 2(3):69–79.

Keylock, C.J. 2005. “Simpson diversity and the Shannon–Wiener index as special cases of a generalized entropy.” *Oikos* 109(1):203–207.

Knight, T.O., and K.H. Coble. 1997. “Survey of US multiple peril crop insurance literature since 1980.” *Review of Agricultural Economics* 19(1):128–156.

Kolmer, J.A. 2001. “Early research on the genetics of Puccinia graminis and stem rust resistance in wheat in Canada and the United States.” In P. D. Peterson, ed. *Stem rust of wheat: from ancient enemy to modern foe.* St. Paul, MN: APS Press, pp. 51–82.

Kolmer, J.A. 2005. “Tracking wheat rust on a continental scale.” *Biotic interactions* 8(4):441–449.

Kolmer, J.A., Y. Jin, and D.L. Long. 2007. “Wheat leaf and stem rust in the United States.” *Australian Journal of Agricultural Research* 58(6):631–638.

Lesser, W., and D.E. Kolady. 2011. “Disease Resistance of Wheat Varieties: Can Private Varieties Withstand the Pressure?” *Economics Research International*. Available at: https://www.hindawi.com/journals/ecri/2011/575192/ [Accessed June 5, 2018].

Lindner, R., A. Fischer, and P. Pardey. 1979. “The time to adoption.” *Economics Letters* 2(2):187–190.

Lobell, D.B., and G.P. Asner. 2003. “Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields.” *Science* 299(5609):1032–1032.

Magurran, A.E., S.R. Baillie, S.T. Buckland, J.M. Dick, D.A. Elston, E.M. Scott, R.I. Smith, P.J. Somerfield, and A.D. Watt. 2010. “Long-term datasets in biodiversity research and monitoring: assessing change in ecological communities through time.” *Trends in Ecology & Evolution* 25(10):574–582.

Makki, S.S., and A. Somwaru. 2001. “Farmers’ participation in crop insurance markets: creating the right incentives.” *American Journal of Agricultural Economics* 83(3):662–667.

Marcon, E., I. Scotti, B. Hérault, V. Rossi, and G. Lang. 2014. “Generalization of the Partitioning of Shannon Diversity.” *PLOS ONE* 9(3):e90289.

McIntosh, R.A., C.R. Wellings, and R.F. Park. 1995. *Wheat Rusts: An Atlas of Resistance Genes*. CSIRO PUBLISHING.

Mendelsohn, R., W.D. Nordhaus, and D. Shaw. 1994. “The Impact of Global Warming on Agriculture: A Ricardian Analysis.” *The American Economic Review* 84(4):753–771.

Millennium Ecosystem Assessment. 2005. *Ecosystems and Human Well-Being: Biodiversity Synthesis*. Washington, DC: Island Press.

Mishra, A.K., R. Wesley Nimon, and H.S. El-Osta. 2005. "Is moral hazard good for the environment? Revenue insurance and chemical input use." *Journal of environmental management* 74(1):11–20.

Mulumba, J.W., R. Nankya, J. Adokorach, C. Kiwuka, C. Fadda, P. De Santis, and D.I. Jarvis. 2012. "A risk-minimizing argument for traditional crop varietal diversity use to reduce pest and disease damage in agricultural ecosystems of Uganda." *Agriculture, Ecosystems and Environment* 157:70–86.

Murphy, D. 2007. *Plant breeding and biotechnology: societal context and the future of agriculture*. Cambridge, UK: Cambridge University Press.

Murphy, J.P., T.S. Cox, and D.M. Rodgers. 1986. "Cluster Analysis of Red Winter Wheat Cultivars Based upon Coefficients of Parentage." *Crop Science* 26(4):672–676.

NASS. 2018. "United States Department of Agriculture National Agricultural Statistics Service: Quick Stats." Available at: https://quickstats.nass.usda.gov/.

National Research Council. 1972. *Genetic vulnerability of major crops*. Washington, DC: National Academy of Sciences.

National Research Council. 1993. *Managing Global Genetic Resources: Agricultural Crop Issues and Policies.* Washington, DC: National Academies Press.

Nelson, C.H., and E.T. Loehman. 1987. "Further toward a theory of agricultural insurance." *American Journal of Agricultural Economics* 69(3):523–531.

NGRP. 2017. "Germplasm Resources Information Network (GRIN)." *National Genetic Resources Program*. Available at: https://www.ars-grin.gov/ [Accessed October 1, 2017].

Pardey, P.G., J.M. Beddow, T.M. Hurley, T.K.M. Beatty, and V.R. Eidman. 2014. "A Bounds Analysis of World Food Futures: Global Agriculture Through to 2050." *Australian Journal of Agricultural and Resource Economics* 58(4):571–589.

Pardey, P.G., J.M. Beddow, D.J. Kriticos, T.M. Hurley, R.F. Park, E. Duveiller, R.W. Sutherst, J.J. Burdon, and D. Hodson. 2013. "Right-Sizing Stem-Rust Research." *Science* 340(6129):147–148.

Pardey, P.G., and V.H. Smith. 2017. "Waste Not, Want Not: Transactional Politics, Research and Development Funding, and the US Farm Bill." Agricultural Policy in Disarray: Reforming the Farm Bill American Enterprise Institute (AEI).

Peterson, P.D. 2001. *Stem rust of wheat: from ancient enemy to modern foe.* St. Paul, MN: APS Press.

PVPO. 2017. "Plant Variety Protection." *Plant Variety Protection Office*. Available at: https://www.ams.usda.gov/services/plant-variety-protection [Accessed October 10, 2017].

Quiggin, J.C., G. Karagiannis, and J. Stanton. 1993. "Crop insurance and crop production: an empirical study of moral hazard and adverse selection." *Australian Journal of Agricultural and Resource Economics* 37(2):95–113.

Rao, C.R. 1982. "Diversity and dissimilarity coefficients: A unified approach." *Theoretical Population Biology* 21(1):24–43.

RMA. 2018. "Federal Crop Insurance Summary of Business Report." Available at: https://www.rma.usda.gov/data/sob.html [Accessed July 18, 2018].

Ruttan, V.W. 1977. "Green Revolution: seven generalizations." *International Development Review* 19(4):16–23.

Shaik, S., K.H. Coble, T.O. Knight, A.E. Baquet, and G.F. Patrick. 2008. "Crop Revenue and Yield Insurance Demand: A Subjective Probability Approach." *Journal of Agricultural and Applied Economics* 40(03):757–766.

Shannon, C.E. 2001. "A Mathematical Theory of Communication." *SIGMOBILE Mob. Comput. Commun. Rev.* 5(1):3–55.

Shaw, L.H. 1964. "The Effect of Weather on Agricultural Output: A Look at Methodology." *Journal of Farm Economics* 46(1):218.

Sherrick, B.J., P.J. Barry, P.N. Ellinger, and G.D. Schnitkey. 2004. "Factors influencing farmers' crop insurance decisions." *American Journal of Agricultural Economics* 86(1):103–114.

Shumway, C.R., R.D. Pope, and E.K. Nash. 1984. "Allocatable fixed inputs and jointness in agricultural production: implications for economic modeling." *American Journal of Agricultural Economics*:72–78.

Simpson, E.H. 1949. "Measurement of diversity." *Nature* 163:688.

Singh, B.D. 2002. *Plant breeding principles and methods*. Ludhiana, New Delhi: Kalyani Publishers.

Singh, R.P., D.P. Hodson, J. Huerta-Espino, Y. Jin, S. Bhavani, P. Njau, S. Herrera-Foessel, P.K. Singh, S. Singh, and V. Govindan. 2011. “The Emergence of Ug99 Races of the Stem Rust Fungus is a Threat to World Wheat Production.” *Annual Review of Phytopathology* 49(1):465–481.

Singh, R.P., D.P. Hodson, Y. Jin, J. Huerta-Espino, M. Kinyua, R. Wanyera, P. Njau, and R. Ward. 2006. “Current status, likely migration and strategies to mitigate the threat to wheat production from race UG99 (TTKS) of stem rust pathogen.” *CAB Reviews: Perspective in Agriculture, Veterinary Science and Natural Resources.* 54:1–13.

Smale, M. 1997. “The Green Revolution and wheat genetic diversity: Some unfounded assumptions.” *World Development* 25(8):1257–1269.

Smale, M., J. Hartell, P.W. Heisey, and B. Senauer. 1998. “The Contribution of Genetic Resources and Diversity to Wheat Production in the Punjab of Pakistan.” *American Journal of Agricultural Economics* 80(3):482–493.

Smale, M., R.E. Just, and H.D. Leathers. 1994. “Land Allocation in HYV Adoption Models: An Investigation of Alternative Explanations.” *American Journal of Agricultural Economics* 76(3):535–546.

Smith, V.H., and A.E. Baquet. 1996. “The demand for multiple peril crop insurance: evidence from Montana wheat farms.” *American Journal of Agricultural Economics* 78(1):189–201.

Smith, V.H., J.W. Glauber, and B.K. Goodwin. 2017. “Time to Reform the US Federal Agricultural Insurance Program.” American Enterprise Institute.

Smith, V.H., and B.K. Goodwin. 1996. “Crop insurance, moral hazard, and agricultural chemical use.” *American Journal of Agricultural Economics* 78(2):428–438.

Smolders, H. ed. 2006. *Enhancing Farmers’ Role in Crop Development: Framework Information for Participatory Plant Breeding in Farmer Field Schools*. Centre for Genetic Resources, the Netherlands: PEDIGREA publication.

Solow, A., S. Polasky, and J. Broadus. 1993. “On the Measurement of Biological Diversity.” *Journal of Environmental Economics and Management* 24(1):60–68.

Solow, A.R., and S. Polasky. 1994. “Measuring biological diversity.” *Environmental and Ecological Statistics* 1(2):95–103.

Stokstad, E. 2007. “Deadly Wheat Fungus Threatens World’s Breadbaskets.” *Science* 315(5820):1786–1787.

Thrupp, L.A. 2000. “Linking Agricultural Biodiversity and Food Security: the Valuable Role of Agrobiodiversity for Sustainable Agriculture.” *International Affairs* 76(2):283–297.

Tilman, D. 2001. “Functional diversity.” *Encyclopedia of biodiversity* 3(1):109–120.

Tsallis, C. 1988. “Possible generalization of Boltzmann-Gibbs statistics.” *Journal of Statistical Physics* 52(1–2):479–487.

Tsallis, C. 1994. “What are the numbers that experiments provide.” *Quimica Nova* 17(6):468–471.

Tuomisto, H. 2012. “An updated consumer’s guide to evenness and related indices.” *Oikos* 121(8):1203–1218.

Upadhyaya, H.K., C.C. David, G.B. Thapa, and K. Otsuka. 1993. “Adoption and productivity impact of modern rice varieties in Nepal.” *The Developing Economies* 31(1):122–137.

USDA-ARS. 2017. “GrainGenes.” Available at: https://wheat.pw.usda.gov/cgi-bin/GG3/browse.cgi [Accessed September 1, 2017].

Vane-Wright, R.I., C.J. Humphries, and P.H. Williams. 1991. “What to protect?—Systematics and the agony of choice.” *Biological conservation* 55(3):235–254.

Velandia, M., R.M. Rejesus, T.O. Knight, and B.J. Sherrick. 2009. “Factors Affecting Farmers’ Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales.” *Journal of Agricultural and Applied Economics; Baton Rouge* 41(1):107–123.

Warwick, R.M., and K.R. Clarke. 1995. “New ‘biodiversity’ measures reveal a decrease in taxonomic distinctness with increasing stress.” *Marine Ecology Progress Series* 129(1/3):301–305.

Weitzman, M.L. 1992. “On Diversity.” *The Quarterly Journal of Economics* 107(2):363–405.

Wellings, C.R. 2011. “Global status of stripe rust: a review of historical and current threats.” *Euphytica* 179(1):129–141.

Whittaker, R.H. 1960. “Vegetation of the Siskiyou Mountains, Oregon and California.” *Ecological Monographs* 30(3):279–338.

Wilby, A., and M.B. Thomas. 2002. “Natural enemy diversity and pest control: patterns of pest emergence with agricultural intensification.” *Ecology Letters* 5(3):353–360.

Wood, D., and J.M. Lenné. 1997. “The conservation of agrobiodiversity on-farm: questioning the emerging paradigm.” *Biodiversity & Conservation* 6(1):109–129.

World Bank. 2011. “Weather index insurance for agriculture: guidance for development practitioners.” Agriculture and rural development discussion paper 50 No. 66274, The World Bank.

van de Wouw, M., T. van Hintum, C. Kik, R. van Treuren, and B. Visser. 2010. “Genetic diversity trends in twentieth century crop cultivars: a meta analysis.” *TAG. Theoretical and Applied Genetics. Theoretische Und Angewandte Genetik* 120(6):1241–1252.

Yu, J., A. Smith, and D.A. Sumner. 2018. “Effects of Crop Insurance Premium Subsidies on Crop Acreage.” *American Journal of Agricultural Economics* 100(1):91–114.

Zegeye, T., G. Taye, D.G. Tanner, H. Verkuijl, A. Agidie, and W.M. Mwangi. 2001. *Adoption of Improved bread wheat varieties and inorganic fertilizer by small-scale farmers in yelmana densa and farta districts of Northwestern Ethiopia*. Mexico: Ethiopian Agricultural Research Organization (EARO) and International Maize and Wheat Improvement Center (CIMMYT).

Zhang, W., T.H. Ricketts, C. Kremen, K. Carney, and S.M. Swinton. 2007. “Ecosystem services and dis-services to agriculture.” *Ecological Economics* 64(2):253–260.