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Adaptability and variety adoption: Implications for plant breeding policy in a changing climate

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Abstract

Adaptability of a seed variety to a wide range of environmental conditions is important in farmers' variety adoption decisions, especially with the increased environmental volatility induced by climate change. Despite the apparent need for information, variety trial reports generally report average relative yields, but they do not provide farmers with measures of variety adaptability. Our theoretical model postulates that the adaptability of seed varieties matters in farmers' variety adoption choices. To test this conjecture, and to measure the magnitude of the effect, we develop a new measure of variety adaptability and estimate an empirical model of adoption in Western Canada. We find that a 1% increase in the adaptability of a variety will increase its adoption by 0.45%. This effect is statistically and economically significant. Our results imply that adding a measure of variety adaptability to *crop variety guides* could enhance the adoption of superior crop varieties, benefiting both farmers and breeders.

KEY WORDS

adaptability, climate change, variety adoption

JEL CLASSIFICATION

L130; Q160; Q180

1 | INTRODUCTION

The lag between variety release and variety adoption is quantitatively important for profitability, consumer welfare, and food security. With the annual world grain and oilseed production over 3 billion tonnes (FAOSTAT, 2020a) and annual genetic gain exceeding 0.8% per year (Li et al., 2018), even a one-year delay in the adoption of the new varieties reduces global production by at least 24 million tonnes per year. For Canada, which currently produces grain and oilseeds worth over USD 17 billion per year (FAOSTAT, 2020b), accelerating the adoption of new varieties by just 1 year would increase the economic surplus by USD 136 million per year, enough resources to fund nearly all Canadian crop breeding.

In making their variety adoption decisions, producers have an incentive to use available information to select the varieties that maximise their expected return. These decisions have become even more complex as climate change makes weather and cropping conditions increasingly variable (Diffenbaugh et al., 2012; Lemmen et al., 2008; Mearns & Norton, 2010; Wheeler & von Braun, 2013). The negative effects of climate variability on agriculture are particularly important for Australia (Anderson, 1979; Anwar et al., 2015; Kingwell, 2006; Ray et al., 2015; Wang et al., 2015). Ray et al. (2015) identify regions where more than 60% of yield variability is attributed to climate variability. These regions include Midwestern U.S. and the Chinese Corn Belt for maize, and Western Europe and Australia for wheat. They also attribute 34%–45% of the variability in wheat yields in countries such as the U.S., Canada, the U.K., Turkey and Argentina to climate variability.

In Australia, Canada, the U.S., the U.K. and several other countries, producers rely heavily on *crop variety guides* generated from public- and producer-funded variety performance trials, where the relative performance of competing varieties is assessed in side-by-side randomised small plot designs.¹ Conventional agronomic advice would typically recommend the adoption of the variety with the highest relative performance in nearby testing sites. However, we show theoretically that this heuristic advice is at best incomplete and can be a misleading indication of the variety with the highest expected performance. Because performance trials are conditioned by the specific weather that occurred at each site in each year, the short history of relative variety performance in any given location may not reflect expected relative performance over the distribution of weather conditions likely to occur at that location. In particular, adaptable seed varieties with an ability to perform reasonably well over a wide range of environmental conditions can have a higher expected yield than a less adaptable variety with superior performance in a specific variety trial. Anecdotally, the ability of a seed variety to adapt to a wide range of environmental conditions, that is, *variety adaptability*, is recognised by crop breeders and has become increasingly important in their variety selection.

To explore this issue empirically, this study develops a new measure, *variety specificity*, which is the mathematical inverse of variety adaptability. Estimating a model for canola variety adoption data for Western Canada, we find that a 1% increase in the adaptability of a variety will increase its adoption by 0.45%. This effect is statistically and economically significant.

Despite this recognition, measures of variety adaptability are typically not reported in the crop variety guides which producers consider when making adoption decisions. Our results suggest that enhanced *ex ante* analysis and reporting of new measures of variety adaptability in these guides could assist producers in making faster and better-informed variety adoption decisions. The findings also have direct implications for the design of and allocation of public, private and producer resources to breeding programmes as well as evaluation and registration processes, especially in the face of climate change.

¹We use *crop variety guide* as a single term to refer to all variety performance reports that exist under various names in different countries, provinces, etc.

In the remainder of this paper, we first provide a review of the literature. The analysis of the relationship between adaptability and adoption is made in three stages: we first present a brief background on the concepts of adaptability and adoption; second, the theoretical relationship between adaptability and adoption is laid out; third, the empirical analysis and results are presented. Last, conclusions and policy recommendations are discussed.

2 | LITERATURE

Since Griliches (1957) and Rogers (1983) provided the cornerstones of the economic literature on agricultural innovation adoption models, many have explored technology adoption in a broader context. Feder et al. (1985), Feder and Umali (1993) and Weersink and Fulton (2020) provide reviews of technology adoption studies. Most of these studies build upon the technology traits that Rogers (1983) recognised as determinants of the rate of adoption.

Profitability, risk and learning are perhaps the most discussed aspects of technology adoption in agriculture. Abadi Ghadim et al. (2005), Cary and Wilkinson (1997), Marra et al. (2003), Michler et al. (2018) and Pannell et al. (2006), for example, examine the effect of expected profitability and relative advantage on the adoption of farm innovations. Weersink et al. (2010) use acreage response models to study the effects of yield potential, risk and climate change patterns on acreage allocation.

Many studies, including some of those mentioned previously, have focussed specifically on the adoption of new crops or varieties of crops. These studies examine seed and farmer characteristics that affect adoption. Dixon et al. (2006) provide a summary of studies that explore adoption of improved wheat varieties in developing countries. Covey (2012) and Dahl et al. (1999) test the effect of relative yield and other factors on adoption of wheat varieties. There is a consensus that relative yield is the most salient determinant of adoption.

Relative yield is generally reported as an average and does not account for yield variability. To tackle this problem, some incorporate a measure of yield or revenue variance in their adoption models (Abadi Ghadim et al., 2005; Barkley & Porter, 1996; Gambrell, 2004). In a mixed-multinomial logit model, Useche et al. (2009) estimate the effects of both seed and farmer/farm characteristics on the adoption of corn seed varieties. They suggest that their methodology can be improved by paying attention to 'differences in yield variances'. There also have been attempts to show that increased volatility due to climate change influences crop yields and thus crop choices (De Giorgi & Pistaferri, 2013).

In addition to the studies mentioned above, many others (Asrat et al., 2010; Cavatassi et al., 2011; Coromaldi et al., 2015; Wale & Yalew, 2007) highlight the importance of variety adaptability in adoption decisions. To the best of our knowledge, however, there have been no attempts to explicitly investigate the role of variety adaptability, as defined in plant breeding, in adoption decisions. This study fills this gap by incorporating the adaptability of seed varieties in farmers' profit-maximisation problem and empirically measuring its effect on variety adoption.

3 | ADAPTABILITY AND ADOPTION

This section presents the conceptual foundations of the relationship between adaptability and adoption. After defining variety adaptability, we discuss how variance can be a misleading measure of adaptability. A new measure of adaptability, variety specificity, is then introduced.

Adaptability refers to genotype \times location (GL) interaction and is defined as 'reduced variation in performance across locations' (Roy & Kharkwal, 2004). Stability, on the contrary, refers to genotype \times year (GY) interaction and is defined as 'reduced variation in

performance across years (Roy & Kharkwal, 2004)². Breeders have traditionally focussed on exploiting the GL interaction rather than the GY interaction or other types of genotype \times environment (GE) interaction. This is because the information obtained from GY interactions is unlikely to be of ‘practical importance’ due to the unpredictability of future weather and climate (i.e. unrepeatability) (Annicchiarico, 2002). Also, in many seed industries (e.g. Canadian canola) varieties are released for only a few years, leaving a short history of temporal variability.

However, in any given year, different locations experience different weather scenarios. Therefore, variations in performance of a variety across various locations, particularly in a vast farming region, reflect how a variety responds to various land characteristics as well as various weather conditions across those locations. As demonstrated in this study, a variety that performs consistently well across various longitudes and latitudes of a vast region in a given year is also more likely to yield consistently well across time than a variety that performs well only under specific conditions or in a specific area.

The key to understanding the importance of adaptability in an individual farmer’s adoption decision lies in the unpredictability of future weather for the farmer. For simplicity, let us assume that there are only two (equally likely) possible weather scenarios, wet and dry, and two available varieties, *A* and *B*. In the closest trial location with wet conditions, Variety *A* has performed 5% higher than Variety *B*. In another more distant trial location with dry conditions, Variety *A* has performed 10% lower than Variety *B*. Without the knowledge of future weather, even a risk-neutral farmer picks Variety *B*—that is, the more adaptable variety—as it has 2.5% higher *expected* performance.

Thus, measurement of variety adaptability will help producers identify the most suitable variety—that is, the one with the highest expected performance. When making varietal choices, producers seldom have much experience with new varieties, and historical data are, by definition, time limited. Similarly, crop variety guides such as seed guides and variety trial reports generally do not report a measure of adaptability for the tested varieties.² Thus, it is left to the farmer to calculate or to form conjectures about the adaptability of different varieties to environmental variability. Farmers could use reported relative performance of the varieties in various (non-mutually exclusive) locations of the farming region to calculate such a measure. In the absence of better information, farmers also rely on their own observations and experience, and professional and social networks (e.g. local input retailers, agronomists and neighbours) to obtain information about the relative performance of different varieties over a distribution of weather conditions. Many Canadian farmers actively participate in social media forums to exchange information about the performance of different technologies including seed. Also, since new varieties are often built upon the old ones, it is possible for farmers to use name, pedigree, technology or even brand of a variety as a proxy for its adaptability.

Economists use yield variance as a regressor in crop adoption models to capture the effect of variability in performance across locations on adoption of crop varieties (Abadi Ghadim et al., 2005; Barkley & Porter, 1996; Gambrell, 2004). Although variance captures overall variability in performance, it can be a misleading measure of adaptability.

Yield variance (and yield average) is often calculated based on the performance across reported test locations or across farms. This often implies a selection bias, because varieties tend to be tested most in locations where they are likely to perform well. Similarly, varieties are only grown by producers who have adopted the technology, not all the potential adopters.

Consider the following example. Canola varieties *A* and *B* are adopted by farmers in equal-size farms on the horizontal (Location) axis in **Figure 1**, as in Hotelling’s linear city model (Hotelling, 1929). The vertical axis represents yield. As it is conventional in Hotelling-type

²See examples of seed guides here: <https://saskseed.ca/seed-guides/>, and examples of canola performance trial reports here: <https://www.canolaperformancetrials.ca/>.

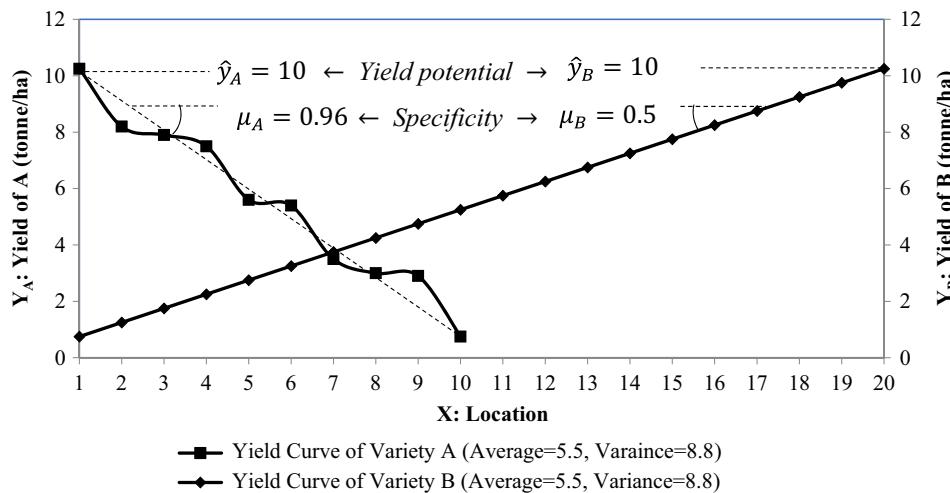


FIGURE 1 Two seed varieties with the same yield average and variance but different adaptability levels. [Colour figure can be viewed at wileyonlinelibrary.com]

models (Malla & Gray, 2005; Torshizi et al., 2018), yield levels are ranked in descending (ascending) order for variety *A* (variety *B*). Variety *A* is designed for locations on the left, while variety *B* is best suited for locations on the right. Canola variety *A* provides higher performance and is seeded in locations 1–6, while *B* provides better performance and is seeded in locations 7–20. To focus on the relationship between variance and adaptability, yield levels are chosen such that the two varieties have the same yield average and variance.

Based on the first and the second moment measures, one might suspect that varieties *A* and *B* are very similar, at least with respect to adoption. However, the two varieties are in fact different; they are bred to respond to different needs, and they have different degrees of adaptability. Variety *A* is clearly less adaptable than *B*—that is, *A* has higher ‘reduced variation in performance across locations’ than *B*—and it is adopted in fewer locations than *B*. Therefore, for the purpose of explaining adoption rates, variance of yield levels may not be an appropriate measure as it may fail to distinguish varieties with respect to their adaptability levels. Specifically, varieties with the same yield variance may not be equally adaptable.

Our proposed measure of adaptability, variety specificity, makes better use of the information presented in Figure 1 by linking adaptability—a plant breeding concept—to the economic literature on product differentiation. Variety specificity is defined as follows: the rate at which the yield of a variety decreases as its area under cultivation expands from the best-yielding location to the second-best location to the third-best location and so on. A variety is considered very specific if its yield drops rapidly when its area expands beyond its top-yielding location. A variety is not considered very specific if it provides consistent yield levels across various locations. In other words, specificity is the mathematical inverse of adaptability; a higher degree of variety specificity implies a lower degree of adaptability.

Graphically, variety specificity is the slope of the curve that is formed when yield levels of a variety in various locations are ranked in descending order. For variety *B* in Figure 1, for example, variety specificity is equal to the slope of its yield curve (0.5). Similarly, for variety *A*, variety specificity is characterised by the slope of a line that best fits its yield curve (0.96). With the higher degree of variety specificity (i.e. higher average rate of drop in yield as the area expands), variety *A* is more specific and, thus, less adaptable than variety *B*.

Assuming yield levels of variety *i* are distributed uniformly as $Y_i \in u(\hat{y}_i, \hat{y}_i)$, where \hat{y}_i and \hat{y}_i are the yield levels of variety *i* in the highest- and lowest-yielding locations, variety specificity for variety *i* is simplified as follows:

$$\mu_i = \frac{\partial Y_i}{\partial X}, \quad (1)$$

when yield levels of variety i , Y_i , are ranked in descending order across locations X .

The uniform distribution assumption is a key to the analysis. In [Figure 1](#), for example, μ_A reflects the overall adaptability of variety A . If the uniform distribution assumption does not hold, μ_A may be a misleading measure of adaptability for variety A . As long as the uniform distribution assumption holds, however, variety specificity is a sufficiently reliable device for measuring adaptability. Chi-squared tests fail to reject the null of uniformity for the yield levels of all the varieties in this study. Yield curve of a canola variety in Manitoba is presented in [Appendix S2](#) as an example. This yield curve is indicative of a uniform distribution. Other common distributions such as normal and beta result in non-linear yield curves. In such cases, adaptability varies across the yield curve and, thus, [Equation \(1\)](#) provides an overall approximation of adaptability. [Torshizi et al. \(2018\)](#) discuss this approximation.

Variety specificity is analogous to *degree of horizontal differentiation* in differentiated product models; a steeper yield curve—that is, a higher degree of variety specificity—implies that the seed variety is more (horizontally) differentiated. This allows for a direct economic interpretation that is rooted in the product differentiation literature—a feature that becomes useful in the theoretical model where we derive the demand for differentiated seed varieties.

The example presented in [Figure 1](#) illustrates that variety specificity can explain the relationship between yield variability and adoption when variance fails to do so, at least for cases similar to the one presented in [Figure 1](#). This leads to a question for empirical research: how prominent are such cases? Or, how well can variety specificity explain the relationship between adaptability and adoption for a broadacre crop?

4 | THEORETICAL MODEL

The objective of the theoretical model is to lay out the theoretical foundations of the relationship between variety adaptability and crop adoption. The complete theoretical model is presented in [Appendix S1](#). In the theoretical model, we first incorporate variety specificity, as a measure of adaptability, in farmers' variety adoption decisions. Next, we derive farmers' demand functions for multiple seed varieties. Seed demand functions are then used in the seed producers' profit-maximisation problem to find the equilibrium conditions. Dictated by the nature of the seed industry, the model allows for differentiated farmers and seed varieties, both differentiated with respect to multiple characteristics.

To incorporate variety specificity in farmers' adoption decisions, we assume that each variety has a yield potential of \hat{y}_i that determines the highest yield level that the variety could potentially reach. Each variety reaches this level at a certain parcel of land. As the area of a variety expands from the best-suited parcel to the second best and so on (not necessarily *around* the best-yielding parcel), the yield of that variety drops. Assuming that land is uniformly distributed between the best-suited and the worst-suited parcels, and that land parcels are arbitrarily small, then the decline in yield of variety i is a continuous and linear function of the amount of land allocated to that variety. Thus, the relationship between yield and area of variety i can be written as:

$$Y_i = \hat{y}_i - \mu_i X_i, \quad (2)$$

where Y_i is the yield of variety i per hectare, \hat{y}_i is the potential yield of variety i per hectare (i.e. yield at the best-suited parcel), X_i is the area or number of parcels allocated to variety i , and μ_i is the decrease in yield of variety i as its area expands by one unit. A graphical illustration of this relationship is presented in [Figure 1](#). This relationship holds for any variety in a region. With a

non-uniform distribution of parcels, the relationship in [Equation \(2\)](#) becomes non-linear, and with parcels that are not arbitrarily small the continuous linear function turns into a step function.

[Equation \(2\)](#) indicates that variety i yields most at a particular parcel of land and its yield drops in a linear fashion by the rate of μ_i as the area—that is, number of parcels—allocated to this variety X_i expands. In other words, μ_i or the yield response of variety i to a change in its corresponding land and environmental characteristic reflects the degree of specificity of variety i . A larger μ_i means that the yield of variety i drops at a higher average rate as its area expands, and this implies that variety i is more specific to particular parcels of land, and vice versa.

The theoretical model uses [Equation \(2\)](#) to form a Lagrangian function for farmers' surplus from varieties $i = 1, \dots, n$ (See [Appendix S1](#) for details). The Lagrangian maximises the region's total surplus by translating the demand for n differentiated varieties into the demand for one production factor, land, and using a single land constraint to find the optimum acreage for each variety. Demand for each variety is then obtained by solving the first-order conditions (FOCs) of the Lagrangian. Demand functions for varieties are used in the seed producers' profit-maximisation problem to find the equilibrium conditions. The Nash equilibrium is found for two, three and then n varieties. The equilibrium conditions lead to at least two propositions regarding farmers' adoption decisions:

Proposition 1 *Assuming the varieties have the same yield potentials, the more specific a variety, the lower its adoption by farmers.*

Proposition 2 *A higher yield potential results in a higher adoption rate for own variety and a lower adoption rate for the rival variety.*

Proofs of these propositions and some corollaries are presented in [Appendix S1](#).

5 | EMPIRICAL ANALYSIS

This section empirically tests [Propositions 1](#) and [2](#), which state the effect of variety specificity and yield potential on the adoption of seed varieties by farmers, respectively. We first describe the calculation of yield potential and variety specificity. Then, the regression model, data, an overview of the industry and estimation results are presented. Finally, we discuss some of the limitations and robustness tests.

5.1 | Calculation of yield potential and variety specificity

Following [Equation \(2\)](#), we start calculating the yield potential and variety specificity for canola seed varieties in each year, by ranking yield levels of each variety in different locations in descending order in a fashion similar to [Figure 1](#). Yield potential of variety i in year t is measured as the yield level of variety i at the highest-yielding location in year t . Variety specificity for variety i in year t is measured as described in [Equation \(1\)](#). Locations refer to rural municipalities (RMs) of Manitoba, Canada. All data originates from farmers' fields rather than trial information. This is because realised yields are likely to be a more reliable source of information to farmers than controlled trials. As mentioned earlier, [Equations \(1\)](#) and [\(2\)](#) assume that yield levels of each variety are distributed uniformly across all locations. Chi-squared tests fail to reject the null of uniformity for all the seed varieties that are used in this study.

It is worth noting that variety specificity of variety i measures the average rate the yield of variety i drops from its highest-, to its lowest-yielding location. Variety specificity is determined by the interaction of seed and land (and environmental) characteristics over a spectrum of locations, not the distance between those locations. By definition, variety specificity aims

to measure whether a variety can be planted in many different locations or is very specific to a certain cluster of locations, regardless of the distance between the locations.

5.2 | Regression model

This study applies a fixed-effects (FEs) panel regression with varieties as FEs to account for the differentiated nature of seed varieties. A poolability *F*-test also indicates that the FEs model is preferred to a pooled model. Results of both panel and pooled regressions are presented in **Table 2** for comparison. The FEs model is also preferable to a random effects model because, firstly, this study is concerned with a specific set of *n* varieties; and secondly, the variety (fixed) effects are likely not independent of the set of regressors. For example, the FEs, which represent characteristics intrinsic to each variety, are likely to affect some of the regressors such as yield potential. The following equation represents the FEs model that is estimated in this study:

$$X_{it} = \alpha + M_{it}\beta + u_{it}; \quad i = 1, \dots, n; t = 1, \dots, T; \quad (3)$$

with *i* denoting seed varieties, *t* denoting time, X_{it} representing the adoption rate of canola variety *i* in Manitoba in year *t*, and M_{it} representing the set of regressors. α is a scalar and β is the set of parameters to be estimated. Baltagi (2005) defines the one-way error component u_{it} as:

$$u_{it} = Z_i\gamma_i + v_{it}, \quad (4)$$

where Z_i is the set of variety dummies that capture observable and unobservable time-invariant seed traits such as brand; γ_i is the set of fixed parameters to be estimated; and v_{it} captures the remainder stochastic disturbances and is assumed to be $IID(0, \sigma_v^2)$. The differential effect of varieties on adoption creates heteroscedasticity. In addition, there is potential for cross-sectional dependency. To estimate standard errors that are corrected for cross-sectional dependence, potential autocorrelation and heteroscedasticity, the Panel Estimated Generalized Least Square (EGLS) method is used along with the Panel Corrected Standard Errors (PCSE) method with the error-variance covariance matrix modelled as cross-section Seemingly Unrelated Regressions (Cross-section SUR) (Reed & Ye, 2011). An advantage of the panel regression approach is that the FEs capture the effect of all time-invariant seed traits.

The dependent variable X_{it} in **Equation (3)** is measured and used in the regression models in two forms: hectares (*Area*) and percentage share (*Market Share*). The set of regressors M_{it} includes the following: the varieties' age as a third-degree polynomial (*T*, T^2 and T^3); the first lag of variety specificity (*Lag Variety Specificity*); the first lag of yield potential (*Lag Yield Potential*); the first lag of relative yield (*Lag Relative Yield*); and the first lag of yield variance (*Lag Variance*). All information-related variables are in lag form to reflect the fact that farmers use the previous year's information to select their varieties for each coming year. The logic behind choosing these regressors is presented below.

5.2.1 | Varieties' age

The concepts of 'diffusion of innovation' and 'S-shaped adoption curves' are key in technology adoption literature (Dixon, 1980; Knudson, 1991; Mahajan & Muller, 1996; Mahajan & Peterson, 1985). Many studies recognise that the length of time that a variety has been in the market as an important determinant of the variety's adoption level (Covey, 2012; Dahl et al., 1999; Gambrell, 2004). Also, the age of a variety is an important determinant of the stage of life cycle of the variety. Following the literature, a third-degree polynomial is used to capture the effect of age, measured in months, on a variety's life cycle.

5.2.2 | Variety specificity and yield variance

Our theoretical framework suggests that the combination of yield potential and variety specificity determines seed varieties' adoption. The impact of variety specificity on adoption has not been explored in the literature. Many have investigated the effect of risk on adoption decisions (Feder, 1980; Fischer et al., 1996; Lindner & Gibbs, 1990). Generally, a measure of variability such as variance is used to incorporate risk in adoption models (Abadi Ghadim et al., 2005). As discussed earlier, however, variance can be a misleading measure of adaptability, at least intuitively and within this context. For comparison purposes, however, we provide estimates of the impact of both variety specificity and yield variance on adoption.

5.2.3 | Yield potential and relative yield

Relative advantage is a key factor in adoption of farm innovations (Abadi Ghadim et al., 2005; Cary & Wilkinson, 1997; Marra et al., 2003; Pannell et al., 2006). The theoretical model demonstrates that a higher yield potential results in a higher adoption rate for a seed variety. Relative yield (ratio of the average yield of a variety to that of a check variety), as a measure of relative advantage, is used in crop adoption models (Abadi Ghadim et al., 2005; Barkley & Porter, 1996; Dahl et al., 1999). For comparison purposes, we estimate the impact of both yield potential and relative yield on adoption.

The impact of other relevant variables on the findings is discussed in Section 5.6.

5.3 | Data

The data set includes acreage, yield levels and age of 42 canola varieties in 105 Rural Municipalities in Manitoba, Canada, from 2004 to 2013—that is, $n = 42$, $T = 10$. After adjustments for 1 missing observation and lags, the estimations are run as unbalanced panels with 377 observations. Data on area and yield are obtained from the Manitoba Agricultural Services Corporation (MASC). Data on the varieties' age are obtained from Canadian Food Inspection Agency's (CFIA) variety registration database.

Summary statistics of the variables are presented in Appendix S2. Average yield potential across the 42 varieties ranges between 2.07 tonnes per hectare in 2007 and 3.07 tonnes per hectare in 2013. Standard deviations suggest very low variation in each year. Average total area of all the varieties in the province ranges from 48,591 hectares in 2006 to 77,773 hectares in 2012, with high standard deviations in most years, suggesting that few varieties in the Canadian canola industry are very successful—some obtain close to half a million hectares—while others fail to capture more than a few thousand hectares. Variety specificity is the lowest (0.41) in 2004 and the highest (0.88) in 2011. The relatively high standard deviations for this variable suggest that the 42 varieties are also quite different with respect to their adaptability levels. Average variety age ranges between 24 and 42 months in 2012 and 2006, respectively. The high standard deviations for this variable suggest that some varieties have much longer life cycles than other.

5.4 | Industry background

After the introduction of hybrid varieties in the late 1990s, the Canadian canola seed industry became highly consolidated. In the study period, most of the market was captured by varieties that contained either Liberty Link (LL) or Roundup Ready (RR), patented herbicide-resistance technologies owned by Bayer and Monsanto, respectively (Malla & Brewin, 2015). Strategic behaviour such as mergers and acquisitions, common ownership, cross-licensing and

joint ventures are common in this industry (Howard, 2009; Malla & Brewin, 2015; Torshizi & Clapp, 2021). During a wave of mergers and acquisitions that took place between 2015 and 2017, Bayer acquired Monsanto and sold LL lines to BASF (Torshizi & Clapp, 2021).

A prime example of a LL variety in our data set is InVigor 5440 (hereafter '5440'), one of the most successful hybrid canola varieties in Canada (MASC, n.d.). Introduced in 2007 under the InVigor brand (Canadian Food Inspection Agency, n.d.), this variety rapidly became popular amongst farmers (Malla & Brewin, 2015). Although not always the highest-yielding variety, 5440 dominated the Canadian canola seed market from 2009 to 2014 and was only discontinued after 2017 (MASC, n.d.). In 2014, 7 years after its introduction, 5440 still had the highest market share in Manitoba (MASC, n.d.). Appendix S4 provides more details on 5440 and the LL technology in general.

Table 1 presents area, market share, variety specificity, yield potential, yield variance and average of canola seed varieties in Manitoba in 2010. Variety specificity is calculated as described in **Figure 1** and **Equation (1)**. At 40%, 5440 has significantly more market share than other varieties, although it does not have the lowest yield variance or the highest yield potential or average. However, this variety has the lowest level of variety specificity, 0.39.

Table 1 also presents other varieties (e.g. 5030, 45H28 and NX4-105 RR) that despite a higher average yield and a lower yield variance than 5440 have very small market shares. These less successful varieties seem to have a higher degree of specificity. Overall, we find that varieties with the highest adoption rate do not necessarily have the highest yield potential, highest average yield or lowest yield variance, but do seem to have a lower degree of specificity. This preliminary glance at variety specificity and adoption of canola varieties suggests that the relationship between these two variables may be worth exploring further.

5.5 | Estimation results

Estimation results are reported in **Table 2**. In models (1)–(3), the dependent variable is adoption as measured by area under cultivation of each variety in hectares. Model (1) is a simple pooled regression that is estimated using OLS. Variety FEs are included in models (2) and (3), while time FEs are rejected by *F*-test. In models (4) and (5), the dependent variable is the market share of each variety in percentage form. Accordingly, a two-limit Tobit approach is used to estimate these models. While models (1), (2) and (4) test the impact of variety specificity and yield potential on adoption, models (3) and (5) are estimated using average and variance of yield levels. Following the theoretical model, variety specificity and yield potential are used together. Similarly, following the literature, average and variance of yield are used together.

We first discuss the findings of the Base model (2) and then make comparisons with the other models. The panel regressions offer a much higher explanatory power than the pooled regression, confirming that importance of variety heterogeneity. As presented in **Table 2**, the regressors in the Base model (2) explain 65% of the variations in adoption of canola seed varieties in Manitoba in the study period. The regression provides plausible signs for all regressors. Also, all variables except the cubic term of a variety's age and the constant are statistically significant at the 99% confidence level. The insignificance of the cubic term is not unexpected, considering the shape of canola varieties' life cycles and their short lives (average of 24–42 months) in the sample. This indicates hill-shaped adoption curves for the varieties.

One may argue that a higher (lower) adoption may result in an increase (decrease) in a variety's age as successful varieties might be kept in the market longer than unsuccessful varieties, potentially creating a reverse causality problem. However, the length of the time a variety is in the market is, to a great extent, predetermined by the seed producer, independent of the

TABLE 1 Descriptive statistics, 2010

Variety	Area (ha)	Market Share (%)	Variety Specificity (kg/ha)	Yield Potential (kg/ha)	Variance	Average (kg/ha)
5440	411,674	40	21.9	2,931.1	683.7	1,776.6
5770	111,491	11	27.5	3,020.7	678.1	1,883.0
5030	59,143	6	31.4	2,712.5	538.0	1,804.6
72-65 RR	57,487	6	31.4	2,746.1	599.7	1,742.9
8440	100,090	10	32.5	3,026.3	666.9	1,911.1
72-55 RR	40,180	4	32.5	2,488.3	543.6	1,552.4
45H28	37,994	4	33.1	2,701.3	532.4	1,838.2
NX4-105 RR	34,882	3	34.7	2,701.3	482.0	1,883.0
9553	27,273	3	36.4	2,533.1	498.8	1,709.3
5020	34,758	3	47.6	2,886.2	723.0	1,647.7
9590	38,160	4	51.0	2,858.2	723.0	1,608.4
1145	31,190	3	67.8	3,149.6	767.8	1,866.2
71-45 RR	11,863	1	71.2	2,421.1	482.0	1,597.2
45H29	13,958	1	81.8	3,110.4	700.5	1,922.3
V1037	17,595	2	86.9	2,443.5	594.1	1,406.7

Source: MASC (n.d.).

success of the variety. That is, when a variety is introduced, the seed producer keeps the variety in the market for several years, regardless of the variety's success. This is because once the variety is developed, tested and registered the cost of keeping the variety in the market (e.g. re-production and bagging costs) is minimal. If the variety is in fact successful, the seed producer might try to develop a new version of the variety—often with an additional trait—that can be sold at a higher price. Also, it is more likely that the length of a variety's life cycle would be determined by its yield potential and variety specificity rather than adoption, *per se*, because adoption itself is a function of yield potential and variety specificity as well. Therefore, it is more likely that lengths of the product cycles are determined by yield potential and degree of variety specificity rather than adoption. Moreover, the age of a variety is recorded at the beginning of each growing season while adoption is recorded after seeding is complete. It is not possible for adoption rates to go back in time and influence a seed producer's decision to whether discontinue a variety. As suggested by Bellemare et al. (2017), this natural sequence in the timing of events removes any concern for reverse causality.

The negative sign for *Lag Variety Specificity* in the Base model (2) in Table 2 provides additional evidence for validity of Proposition 1 regarding the negative relationship between variety specificity and adoption. Variety specificity indicates how many kilograms of yield, on average, are sacrificed as the area allocated to a variety expands from the highest-yielding location to the second-best location and so on. The estimated parameter for this variable suggests that, in our sample, a 1-kilogram increase in variety specificity results in an average 869.5 hectare decrease in adoption of a variety.

Farmers are likely to look at yield potential of a variety when deciding which varieties of canola to grow. As presented in the Base model (2) in Table 2, the estimated parameter for *Lag Yield Potential* suggests that, for an average variety in our sample, 1 kilogram per hectare increase in yield potential results in approximately 21.6 hectares increase in adoption.

The elasticities for variety specificity and yield potential are calculated to be -0.45 and 0.86, respectively. The relative magnitude of elasticities provides a key insight for breeders: farmers

TABLE 2 Estimation results

Dependent Variable:	Area (ha)		Area (ha)		Area (ha)		Market Share (%)	
Estimation Method:	Pooled		Panel Least Squares-FEs (Cross-Section SUR PCSE)		Panel Least Squares-FEs (Cross-Section SUR PCSE)		Two-Limit Tobit (Lower bound=0, Upper bounds=0.45)	
Model #	1	2 (Base)		3		4		5
<i>Lag Variety Specificity</i>	-1,405.0*** (191.7)	-869.5*** (206.4)	-	-	-0.0012** (0.0005)	-	-	-
<i>Lag Yield Potential</i>	31.5*** (4.1)	21.6*** (4.1)	-	-	0.000016* (0.000009)	-	-	-
<i>Lag Variance</i>	-	-	-40.9* (24.2)	-	0.00004 (0.00005)	-	-	-
<i>Lag Relative Yield</i>	-	-	37.8/0.7*** (12,223)	-	-0.02 (0.03)	-	-	-
<i>T</i>	3,579.8*** (676.9)	3,530.6*** (652.0)	3,683.2*** (717.8)	0.02*** (0.002)	0.02*** (0.002)	0.02*** (0.002)	0.02*** (0.002)	0.02*** (0.002)
<i>T</i> ²	-82.3*** (25)	-76.8*** (28.3)	-68.3*** (30.6)	-0.0004*** (0.001)	-0.0004*** (0.001)	-0.0004*** (0.001)	-0.0004*** (0.001)	-0.0004*** (0.001)
<i>T</i> ³	0.47** (0.23)	0.37 (0.27)	0.28 (0.29)	0.0000026*** (0.000004)	0.0000026*** (0.000004)	0.0000026*** (0.000004)	0.0000026*** (0.000004)	0.0000026*** (0.000004)
<i>Constant</i>	450.5 (2450.9)	2,695.7 (1,966.2)	2,082.9 (1,701.9)	-0.15*** (0.02)	-0.15*** (0.02)	-0.15*** (0.02)	-0.15*** (0.02)	-0.15*** (0.02)
R-Sq.	0.44	0.65	0.63	-	-	-	-	-
Adj. R-Sq.	0.44	0.61	0.58	-	-	-	-	-
Wald Chi Sq.	-	-	-	207.2***	199.7***	199.7***	199.7***	199.7***
Cross-Sections	42	42	42	42	42	42	42	42
Periods	9	9	9	9	9	9	9	9
Observations	377	377	377	377	377	377	377	377

Source: Authors' estimation. Note: Asterisks denote significance at the 10%, 5%, and 1% levels.

are willing to trade 1% yield potential for 1.91% increase in adaptability. In other words, if a new variety is 1.9% less adaptable than an old one, it must have a yield potential that is at least 1% higher for it to have the same adoption rate as the old one.

Results of the two-limit Tobit model (4) are consistent with those of the FE model (2). Both models suggest that a higher degree of variety specificity results in lower adoption and a higher yield potential results in higher adoption, although the estimated parameter for yield potential is significant only at the 90% confidence level. Similarly, the estimated parameters of the pooled model (1) are consistent with those of the FE model (2).

Overall, comparisons of the Base FE model (2) with the pooled model (1) and the Tobit model (4) reveal two points. First, the findings of this study regarding the negative effect of variety specificity and positive effect of yield potential on adoption hold whether the dependent variable is measured in hectare or in percentages. Second, these findings hold whether the specification is pooled, FE or two-limit Tobit.

Model (3) replaces *Lag Variety Specificity* and *Lag Yield Potential* with *Lag Variance* and *Lag Relative Yield*. The estimated parameters in model (3) have plausible signs. However, the *Lag Variance* in this model has a lower significance level compared with the *Lag Variety Specificity* in model (2). Similarly, the *t*-statistic for *Lag Relative Yield* in model (3) is 3.1, which is significantly less than 5.3 for *Lag Yield Potential* in model (2). Also, model (3) provides lower *R*-squared and Adjusted *R*-squared compared with model (2). Similar evidence can be found from comparison of models (4) and (5). Overall, these comparisons reveal that, at least in the data set that is used in this study, variety specificity and yield potential are better determinants of farmers' adoption choices than yield variance and average.

Fixed-effects vector decomposition (FEDV), presented in Appendix S4, allows us to discuss the role of variety heterogeneity and different technologies and brands in adoption. The FEVD reveals that in the canola seed industry very few varieties become extremely successful while most varieties struggle; only 8 out of the 42 varieties have positive FEs. Even within those 8 varieties, the FE of the top variety is larger than the next 5 combined.

5.6 | Limitations and robustness tests

In this section, we first explain why some potentially relevant variables are not included in the empirical analysis and whether their exclusion could affect the main findings. Then, we discuss the results of multiple robustness tests.

5.6.1 | Agronomic traits and seed brands

Agronomic traits such as resistance to certain diseases, height and standability could affect variety adoption. Similarly, it may be argued that certain seed producers are more popular amongst canola producers, especially if their previous varieties have been successful. The effect of agronomic traits and seed brands on adoption is not the primary focus of this study. Nevertheless, one may be concerned about whether leaving out these variables would create an omitted variables problem and bias the results. Agronomic traits and seed brands, however, are time invariant. For example, if a variety's resistance level to a certain disease is reported as 'susceptible', the level of resistance does not change over time and is reported as 'susceptible' in various years' seed guides. This is particularly true for canola varieties because they are hybrids. The time-invariant factors are captured by the variety FEs and, therefore, do not cause a bias in the estimated parameters. Nevertheless, the FEVD in Appendix S4: Table D.1 provides some insights into the effect of seed producer brands on adoption.

5.6.2 | Varieties' price

The theoretical model endogenises the effect of seed prices on adoption in exogenous variables. As illustrated in Appendix S1: Equation (A.13), variety prices are a function of exogenous variables including yield potential and variety specificity. Appendix S1: Equation (A.14) indicates that equilibrium adoption for a variety is a function of the same set of exogenous variables. As such, it is redundant to include the variety seed prices variable in a regression model that estimates the adoption rate of seed varieties and already includes yield potential levels and variety specificity as regressors. Also, prices for individual canola seed varieties in Canada are not available.

5.6.3 | Relative yield potential and relative variety specificity

To remain consistent with the theoretical model, absolute values of the yield potential and variety specificity are used in the regression models in Table 2. Nevertheless, a regression analysis is also performed using relative yield potential and relative variety specificity. The results, presented in Appendix S3, confirm the main findings of the study.

5.6.4 | Number of available varieties

The theoretical model demonstrates that adoption of each variety is also a function of the number of available varieties in the market. Number of available varieties in the study period does not vary significantly. Thus, this variable is not used in the Base model. Nevertheless, Appendix S3 examines the effect of this variable. Results indicate that this variable is not statistically significant and including it in the model changes the estimated parameters for variety specificity and yield potential by a negligible amount.

5.6.5 | Cross-sectional weights

The main regressions presented in Table 2 assume equal weights for all the different varieties (cross sections). As presented in the FEVD in Appendix S4: Table D.1, however, a handful of canola seed varieties in the market are significantly more successful than others. Appendix S3 examines the possibility that allocating different weights to different varieties based on their adoption rates would affect the findings. Results indicate that variety heterogeneity is important and allowing for cross-section weights could result in a higher explanatory power. Nevertheless, allowing for cross-section weights does not change the previous findings regarding the impact of variety specificity and yield potential on adoption.

5.6.6 | Time fixed effects

Although time FEs are rejected by the *F*-test, Appendix S3 tests whether including time FEs would change the main findings. Including time FEs results in a negligible change in the estimated parameters of the Base model (2).

Overall, the robustness tests presented in Appendix S3 and the results of models (1) and (4) validate the main findings regarding the impact of variety specificity and yield potential on adoption. Also, these tests suggest that the results of the Base model (2) are highly robust.

6 | CONCLUSIONS AND POLICY RECOMMENDATIONS

Variety adoption decisions are important to farmers' income. Farmers can often choose from dozens of differentiated seed varieties that embody various traits making the decision to adopt a variety that suits a farmer's land a difficult one. There is some urgency in the producers' adoption decisions because new varieties on average perform better than older varieties. As such, a significant opportunity cost is associated with postponing a decision to adopt a new variety until several years of local performance data are available.

While conventional agronomic advice would typically recommend the adoption of the variety with the highest relative performance in nearby testing sites, we show theoretically that this heuristic advice is at best incomplete and can be a misleading indication of the variety with the highest expected performance. This is due to the unpredictability of environmental conditions. Because performance trials are conditioned by the specific weather that occurred at each site in each year, the highest performing variety at any given location may not reflect expected relative performance over the distribution of weather conditions likely to occur at that location. More adaptable seed varieties with an ability to perform reasonably well over a wide range of environmental conditions can have higher expected yield than a less adaptable variety with similar historical performance at a specific location.

Our empirical results also indicate that varietal adaptability influences producer adoption. Our data set includes acreage, yield levels and age of 42 canola varieties in 105 Rural Municipalities in Manitoba, Canada, from 2004 to 2013. The reported yield data are used to develop an index of *specificity* for each variety, which is the inverse of *variety adaptability*. Under a number of alternative specifications and robustness checks, the results indicate that variety adaptability has a positive (and statistically significant) effect on variety adoption. This effect is also economically significant as the estimated coefficients imply large impacts on variety adoption. A 1% increase in adaptability (or reduction in specificity) of a variety will increase its adoption by 0.45%. Each year, over 8 million hectares of land is allocated to canola in Canada (Statistics Canada, 2022). It is not unusual for some varieties to cover several million hectares of land (Malla & Brewin, 2015). As such, the estimated effect suggests that adaptability is an important factor considered by producers in their adoption decisions. As we discuss below, this large response to adaptability could be somewhat muted by incomplete producer information.

When making varietal choices, producers seldom have much experience with new varieties, and historical data are, by definition, time limited. To assist producers with variety selection, reports of independent randomised variety performance trials are published each year by either producer or government bodies. Seed marketers and farmers rely on these guides to identify new varieties with the greatest potential for their farm. These guides typically report the average yield of each variety and other phenotypic information (or yield relative to a check variety) within specific regions or at specific test locations.

Ironically, however, these guides generally do not report a measure of adaptability for the varieties. Thus, it is left to the farmer to calculate or to form conjectures about the adaptability of different varieties to environmental variability. It is recommended that the institutions that provide farmers with crop variety guides present farmers with information regarding the adaptability of the available varieties. This will help farmers make more informed decisions in an increasingly volatile climate. This will also speed up the adoption of new and often superior varieties, benefiting both farmers and breeders.

Great efforts are made to improve the yield levels of various crops. Very often, however, these efforts result in seed varieties that perform well under specific conditions and, therefore, are rejected by most farmers. In the data set used in this study, for example, out of 42 varieties,

the top three varieties capture 39% of the total area while 24 varieties capture less than 1% of the area each over the 2004–2013 period. The findings have a clear message for plant breeders: adaptability is important to farmers, and it is likely to become even more important as climate change exacerbates environmental variability. As such, there should be further emphasis on variety adaptability, rather than performance under specific conditions, in the design of the breeding programmes. Regulatory agencies can facilitate this process by considering measures of adaptability in the evaluation and registration of new varieties. While this would reduce the producers' choice set to more adaptable varieties, it would also reduce the incentives and the ability of breeders to licence a variety based on hand-picked results. Correcting this asymmetry of information would increase the incentives of private and public breeders to incorporate adaptability into their breeding objectives.

While our empirical analysis was confined to one crop in one province in Canada, the context for the study is not at all unique. Many regions of the world are subject to a great deal of weather variation that is anticipated to increase with climate change. The use of independent regional randomised plot trials, as a tool to foster faster and better-informed adoption of crop varieties, exists for many crops in many countries (e.g. France, UK, Germany, Australia, Canada and the U.S.). To our knowledge, measures of variety adaptability are not included in any of the reports of these trials. At the very least, we are posing a research question of whether additional measurement and reporting of variety adaptability would benefit these crop innovation systems.

Further research is needed on the effect of adaptability on adoption of agricultural innovations, particularly in the seed sector. Evidence from various crops in different countries can attract the attention of stakeholders. This is particularly important as climate change brings about more volatility in weather conditions. As mentioned in the Introduction, there is a growing body of evidence linking climate change and yield variability. A theoretical framework can be employed to further extend this link to the seed producers' incentives in the face of increased volatility. Effects on competition, pricing and incentives to invest under different institutional settings (e.g. end-point royalty versus market price systems) are also worth exploring. While we discuss only two measures of adaptability, variance and degree of specificity, the suitability of other measures such as those used in risk models should be investigated.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in Variety yield data browser at https://www.masc.mb.ca/masc.nsf/mmpp_browser_variety.html. These data were derived from the following resources available in the public domain: Manitoba Agricultural Services Corporation, <https://www.masc.mb.ca>. The data that support the findings of this study are also available from the corresponding author upon reasonable request.

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REFERENCES

Abadi Ghadim, A.K., Pannell, D.J. & Burton, M.P. (2005) Risk, uncertainty, and learning in adoption of a crop innovation. *Journal of Agricultural Economics*, 33(1), 1–9.

Anderson, J.R. (1979) Impacts of climatic variability in Australian agriculture: a review. *Review of Marketing and Agricultural Economics*, 47(3), 147–177.

Annicchiarico, P. (2002) Genotype \times environment interactions – challenges and opportunities for plant breeding and cultivar recommendations. *FAO Plant Production and Protection Paper – 174*. Rome: Food and Agriculture Organization of the United Nations.

Anwar, M.R., Li Liu, D., Farquharson, R., Macadam, I., Abadi, A., Finlayson, J. et al. (2015) Climate change impacts on phenology and yields of five broadacre crops at four climatologically distinct locations in Australia. *Agricultural Systems*, 132, 133–144.

Asrat, S., Yesuf, M., Carlsson, F. & Wale, E. (2010) Farmers' preferences for crop variety traits: lessons for on-farm conservation and technology adoption. *Ecological Economics*, 69(12), 2394–2401.

Baltagi, B. (2005) *Econometric analysis of panel data*, 3rd edition. Chichester: John Wiley & Sons Ltd.

Barkley, A.P. & Porter, L.L. (1996) The determinants of wheat variety selection in Kansas, 1974–1993. *American Journal of Agricultural Economics*, 78(1), 202–211.

Bellemare, M., Masaki, T. & Pepinsky, T. (2017) Lagged explanatory variables and the estimation of causal effect. *The Journal of Politics*, 79(3), 949–963.

Canadian Food Inspection Agency. (n.d.) Varieties of crop kinds registered in Canada. Ottawa, ON: Government of Canada. Available from: http://www.inspection.gc.ca/active/netapp/regvar/regvar_lookupe.aspx. [Accessed 15th August 2022].

Cary, J.W. & Wilkinson, R.L. (1997) Perceived profitability and farmers' conservation behaviour. *Journal of Agricultural Economics*, 48(1), 13–21.

Cavatassi, R., Lipper, L. & Narloch, U. (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.

Coromaldi, M., Pallante, G. & Savastano, S. (2015) Adoption of modern varieties, farmers' welfare and crop biodiversity: evidence from Uganda. *Ecological Economics*, 119(C), 346–358.

Covey, C. (2012) Coop-performance variety trials: information asymmetries in the Western Canadian CWRS wheat industry. M.Sc. Thesis. Saskatoon, SK: University of Saskatchewan.

Dahl, B.L., Wilson, W.W. & Wilson, W.W. (1999) Factors affecting spring wheat variety choices: comparisons between Canada and the United States. *Canadian Journal of Agricultural Economics*, 47(3), 305–320.

De Giorgi, G. & Pistaferri, L. (2013) Climate change volatility and crop choices. International Growth Centre Working Paper. London: London School of Economics.

Diffenbaugh, N.S., Hertel, T.W., Scherer, M. & Verma, M. (2012) Response of corn markets to climate volatility under alternative energy futures. *Nature Climate Change*, 2(7), 514–518.

Dixon, R. (1980) Hybrid corn revisited. *Econometrica*, 48(6), 1451–1461.

Dixon, R., Nalley, L., Kosina, P., La Rovere, R., Hellin, J. & Aquino, P. (2006) Adoption and economic impact of improved wheat varieties in the developing world. *Journal of Agricultural Science*, 144(6), 489–502.

Feder, G. (1980) Farm size, risk aversion and the adoption of new technology under uncertainty. *Oxford Economic Papers*, 32(2), 263–283.

Feder, G., Just, R.E. & Zilberman, D. (1985) Adoption of agricultural innovations in developing countries: a survey. *Economic Development and Cultural Change*, 33(2), 255–298.

Feder, G. & Umali, D.L. (1993) The adoption of agricultural innovations: a review. *Technological Forecasting and Social Change*, 43(3–4), 215–239.

Fischer, A.J., Arnold, A.J. & Gibbs, M. (1996) Information and the speed of innovation adoption. *American Journal of Agricultural Economics*, 78(4), 1073–1081.

Food and Agriculture Organization. (2020a) FAOSTAT statistical database: crops. Rome: United Nations.

Food and Agriculture Organization. (2020b) FAOSTAT statistical database: value of agricultural production. Rome: United Nations.

Gambrell, S. (2004) Predicting the life cycle of rice varieties in Texas. M.Sc. Thesis. College Station, TX: Texas A&M University.

Griliches, Z. (1957) Hybrid corn: an exploration in the economics of technological change. *Econometrica*, 25(4), 501–522.

Hotelling, H. (1929) Stability in competition. *Economic Journal*, 39(153), 41–57.

Howard, P. (2009) Visualizing consolidation in the global seed industry: 1996–2008. *Sustainability*, 1(4), 1266–1287.

Kingwell, R.S. (2006) Climate change in Australia: agricultural impacts and adaptation. *Australasian Agribusiness Review*, 14, 1–19.

Knudson, M.K. (1991) Incorporating technological change in diffusion models. *American Journal of Agricultural Economics*, 73(3), 724–733.

Lemmen, D.S., Warren, F.J., Lacroix, J. & Bush, E. (2008) From impact to adaptation: Canada in a changing climate 2007. Ottawa, ON: Government of Canada.

Li, H., Rasheed, A., Hickey, L. & He, Z. (2018) Fast-forwarding genetic gain. *Trends in Plant Science*, 23(3), 184–186.

Lindner, R. & Gibbs, M. (1990) A test of Bayesian learning from farmer trials of new wheat varieties. *Australian Journal of Agricultural Economics*, 34(1), 21–38.

Mahajan, V. & Muller, E. (1996) Timing, diffusion, and substitutions of successive generations of technological innovations: the IBM mainframe case. *Technical Forecasting and Social Change*, 51(2), 109–132.

Mahajan, V. & Peterson, R.A. (1985) *Models for innovation diffusion*. Beverly Hills, CA: Sage Publications.

Malla, S. & Brewin, D. (2015) The value of a new biotechnology considering R&D investment and regulatory issues. *AgBioforum*, 18(1), 6–25.

Malla, S. & Gray, R. (2005) The crowding effects of basic and applied research: a theoretical and empirical analysis of an agricultural biotech industry. *American Journal of Agricultural Economics*, 87(2), 423–438.

Manitoba Agricultural Services Corporation. (n.d.) Variety yield data browser. Winnipeg, MB: Manitoba Management Plus Program, Manitoba Agricultural Services Corporation. Available from: https://www.masc.mb.ca/masc.nsf/mimpp_browser_variety.html. [Accessed 15th August 2022].

Marra, M., Pannell, D.J. & Abadi Ghadim, A.K. (2003) The economics of risk, uncertainty, and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Journal of Agricultural Systems*, 75(2–3), 215–234.

Mearns, R. & Norton, A. (2010) The social dimensions of climate change: equity and vulnerability in a warming world. Washington, DC: The World Bank Group.

Michler, J., Tjernstrom, E., Verkaart, S. & Mausch, K. (2018) Money matters: the role of yields and profits in agricultural technology adoption. *American Journal of Agricultural Economics*, 101(3), 710–731.

Pannell, D.J., Marshall, G.R., Barr, N., Curtis, A., Vanclay, F. & Wilkinson, R. (2006) Understanding and promoting adoption of conservation practices by rural landholders. *Australian Journal of Experimental Agriculture*, 46(11), 1407–1424.

Ray, D.K., Gerber, J.S., MacDonald, G.K. & West, P.C. (2015) Climate variation explains a third of global crop yield variability. *Nature Communications*, 6(1), 1–9.

Reed, W.R. & Ye, H. (2011) Which panel data estimator should I use? *Applied Economics*, 43(8), 985–1000.

Rogers, E.M. (1983) Diffusion of innovations, 3rd edition. New York, NY: The Free Press.

Roy, D. & Kharkwal, M.C. (2004) Breeding for wider adaptability. In: Jain, H.K. & Kharkwal, M.C. (Eds.) *Plant breeding mendelian to molecular approaches*. Berlin: Springer Science+Business Media Dordrecht.

Statistics Canada. (2022) *Table 32-10-0359-01, estimated areas, yield, production, average farm price and total farm value of principal field crops, in metric and imperial units*. Available from: <https://doi.org/10.25318/3210035901-eng>

Torshizi, M. & Clapp, J. (2021) Price effects of common ownership in the seed sector. *The Antitrust Bulletin*, 66(1), 39–67.

Torshizi, M., Gray, R. & Fulton, M. (2018) Non-linear demand in linear town. *Journal of Agricultural and Food Industrial Organization*, 16(2), 1–12.

Useche, P., Barham, B. & Foltz, J. (2009) Integrating technology traits and producer heterogeneity: a mixed-multinomial model of genetically modified corn adoption. *American Journal of Agricultural Economics*, 91(2), 444–461.

Wale, E. & Yalem, A. (2007) Farmers' variety attribute preferences: implications for breeding priority setting and agricultural extension policy in Ethiopia. *African Development Review*, 19(2), 379–396.

Wang, B., Chen, C., Li Liu, D., Asseng, S., Yu, Q. & Yang, X. (2015) Effects of climate trends and variability on wheat yield variability in eastern Australia. *Climate Research*, 64(2), 173–186.

Weersink, A., Cabas, J.H. & Olale, E. (2010) Acreage response to weather, yield, and price. *Canadian Journal of Agricultural Economics*, 58(1), 57–72.

Weersink, A. & Fulton, M. (2020) Limits to profit maximization as a guide to behavior change. *Applied Economic Perspectives and Policy*, 42(1), 67–79.

Wheeler, T. & von Braun, J. (2013) Climate change impacts on global food security. *Science*, 341(6145), 508–513.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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