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Article

Precipitation causes quality losses of large economic relevance in wheat production

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Abstract

Adverse weather conditions can affect both crop yield quantity and yield quality. In wheat production, especially the risk of a downgrading due to low baking quality, as indicated by the Hagberg Falling Number, can cause large economic losses after precipitation events. We here estimate precipitation effects on the risk of such a downgrading and quantify the resulting economic losses. To this end, we leverage a panel dataset from the Swiss wheat varieties trial network (N = 1,859) and high-quality weather data. We use a fixed effects estimation framework to estimate precipitation effects and simulate economic losses. We find that precipitation close to harvest significantly increases the risk of a downgrading due to low baking quality. Moreover, downgrading events cause large revenue reductions of up to 1,445 Swiss francs per hectare. This adds new economic insights, highlights the role of weather-dependent crop quality, and provides a basis to improve risk management.

Keywords: Risk management, Crop quality, Wheat, Downgrading, Pre-harvest sprouting

JEL code: Q1

1 Introduction

Adverse weather conditions are among the most important production risks in crop production and climate change is amplifying these risks (Barnabás et al. 2008; Lobell et al. 2011a; Ray et al. 2015; Lesk et al. 2016; Ortiz-Bobea et al. 2021). Adverse weather conditions lead to reductions of crop yield quantity (Schlenker and Roberts 2009; Trnka et al. 2014; Webber et al. 2018), and additionally can reduce price-relevant crop quality (Pereyra-Irujo and Aguirrezábal 2007; Lanning et al. 2011; Diacono et al. 2012). This puts farmers' profitability at risk but has also implications for other actors such as seed traders and breeders, downstream actors such as processors and retailers, insurance providers, and policymakers. Economic assessments of weather risks for price-relevant crop quality are therefore essential to improve decision making in the agri-food sector.

We here provide an assessment of weather-induced wheat quality losses. More specifically, we identify precipitation effects on the risk of downgrading due to low baking quality, as indicated by the Hagberg Falling Number, and quantify its economic relevance. To this end, we use a panel dataset from the official Swiss winter wheat varieties trial network consisting of 1,859 observations of commercially available winter wheat varieties recorded at ten representative sites from 2008 to 2019.

Previous research has provided economic risk assessments of weather effects on price-relevant crop quality, but it remains a comparatively unexplored research area. For example, Kawasaki and Uchida (2016) highlight weather-dependent quality effects on the economic performance of rice production in Japan, Lyman and Nalley (2013) and Nalley et al. (2016) of rice production in the USA, Dalhaus et al. (2020) of apple production in Switzerland, and Ramsey et al. (2020) of peanut production in the USA. A risk assessment of weather-dependent quality effects on the economic performance of wheat production remains an open research area. However, wheat is among the most widely grown crops in the world and is the most widely grown crop in European and Swiss agriculture (FOAG 2021). The producer price of wheat also depends on weather-dependent quality at harvest (Mares and Mrva 2014). Previous research has identified that especially precipitation close to harvest can reduce the baking quality of bread and biscuit wheat and results in a downgrading to animal feed wheat (Biddulph et al. 2008; Mares and Mrva 2008; Barnard and Smith 2012). Globally, such a downgrading is expected to be among the economically most important quality-related risks for wheat producers. For example, it causes annual losses of up to 1 billion US dollars because animal feed wheat has a lower producer price than bread and biscuit wheat (Bewley et al. 2006; Moore et al. 2017; Shao et al. 2018; Cannon et al. 2022). For instance, in the US Pacific Northwest, there is a price reduction of $0.25 per bushel for every 25 s below 300 s (Steber 2017), of $AUS 20–30 per ton for a Hagberg Falling Number below 300 s in Australia (Biddulph et al. 2008; Newberry et al. 2018). In the here used case study of Swiss wheat production, there is a price reduction of up to 30 per cent for a Hagberg Falling Number below 220 s (swiss granum 2021, 2022).

This paper has two objectives. Firstly, we estimate precipitation effects on the risk of a downgrading of high-quality bread and biscuit winter wheat to lower quality animal feed wheat due to a precipitation induced low Hagberg Falling Number, which is an internationally standardized indicator for low baking quality in the industry. Secondly, we assess the economic relevance of such a downgrading for wheat producers by simulating resulting revenue reductions. Switzerland is a highly relevant case study, as Swiss wheat production is highly exposed to wheat quality-related risks. For example, many winter wheat producers throughout Switzerland experienced Hagberg Falling Number scores below the critical threshold of 220 s in the rainy summer of 2014 so that approximately 25 per cent of the national bread and biscuit wheat harvest was downgraded to feed wheat (swiss granum 2021).

We here leverage a panel dataset from the official Swiss winter wheat varieties trial network because such data are insightful when data from practice are limited (Lobell et al. 2011b), as it is the case for the Hagberg Falling Number in winter wheat production. To estimate precipitation effects on the risk of a downgrading due to a low Hagberg Falling Number, we build a two-way fixed effects (variety and site fixed effects) reduced-form model based on agronomic findings (see Section 2.3 Agronomic background) that also controls for temperature exposure. The model supports the identification of precipitation effects because it uses only exogenous explanatory weather variables, controls for a myriad of potential confounders and implicitly accounts for short-term management adaptations as a response to risk exposure (e.g. harvest before full ripeness when precipitation is forecasted). Field trial data support the identification of precipitation effects because we can match high-quality weather data with exact field locations and exclude potentially confounding effects of changing input and output prices because field management is standardized and follows best practice (see Section 4.1). To assess the economic relevance of a downgrading risk, we simulate resulting revenue reductions and illustrate the historical frequency of downgrading events.

This paper has three core results. First, precipitation close to harvest, i.e. when precipitation amounts barely affect wheat yield quantity (Barnabás et al. 2008; Farooq et al. 2014; Varga et al. 2015), increases the risk of a downgrading of bread and biscuit wheat to animal feed wheat. More specifically, we estimate that each millimeter of precipitation aggregated over the 31 days prior to harvest increases the risk of a downgrading by approximately 0.1 percentage points. Historically, this has increased the risk of a downgrading by up to 26.74 percentage points in our sample. Second, a downgrading to feed wheat due to a low Hagberg Falling Number causes large economic losses for farmers. We estimate historical revenue reductions of up to 1,445 Swiss francs per hectare in our sample (representing ca. 40 per cent of the total expected revenue). Third, such downgrading events occur rarely and not on a regular basis. The risk of a downgrading due to a low Hagberg Falling Number can be idiosyncratic (only few observations with a downgrading within a location and year) or systemic (many observations with a downgrading within and across locations in the same year). On average, we find that the expected loss due to precipitation-induced downgrading of wheat is 52 Swiss francs per hectare across all observations.

The remainder of the paper is structured as follows. We first provide an economic and agronomic background of the risk of a downgrading due to a low Hagberg Falling Number and introduce the Swiss wheat market. Building on this, we present the estimation and identification strategy used to quantify precipitation effects on the risk of a downgrading and simulation of revenue reductions. We then put forward our data section, followed by the results. Next, we discuss the external validity of our findings and management options to cope with the risk of a downgrading at farm level. Finally, we end the paper with concluding remarks and policy recommendations.

2 Background

This section presents background information of how crop quality affects farmers' profits through producer prices, introduces the Swiss wheat market, and provides an agronomic background about weather effects on the Hagberg Falling Number, the industry's standardized indicator for low baking quality, also with the aim to motivate our model selection.

2.1 Economic background

Crop quality is an important determinant of producer prices ultimately affecting profits (Dalhaus et al. 2020). The effect of low crop quality on profits is illustrated in Equation (1), in which $\Delta\pi_{it}$ denotes the difference in crop profits of farmer i in year t due to a quality-induced change in the producer price Δp_{it} (Dalhaus et al. 2020) and under the *ceteris paribus* assumption.

$$\Delta\pi_{it} = \Delta p_{it}\,(q_{it}) * y_{it} - \Delta c_{it}\,(q_{it}) \quad (1)$$

The change in the producer price Δp_{it} depends on the crop yield quality q (Stiegert and Blanc 1997; Dalhaus et al. 2020; Ramsey et al. 2020; Roberts et al. 2022) and is multiplied by the crop yield quantity y_{it}, i.e. changes in yield quality can affect revenues. A potential change in production costs Δc_{it} can result from changes in field management that affect crop yield quality q. Next to management decisions, exogenous and random weather conditions can also affect crop yield quality (e.g. Lanning et al. 2011; Barnard and Smith 2012; Dalhaus et al. 2020). In the reverse direction, weather conditions and field management can affect production costs and crop yield quality ultimately reflected in the producer price and thereby affect crop profits.

In the context of this paper, we focus on Swiss winter wheat production, where bread and biscuit wheat with a Hagberg Falling Number below 220 s is downgraded to animal feed wheat. This causes an abrupt price reduction Δp_{it}, thereby reducing revenues and ultimately profits.[1] The Hagberg Falling Number is a downside risk, i.e. there is no price reward for test results above 220 s.

2.2 The Swiss wheat market

Wheat is the most widely grown crop in Switzerland and covers approximately 50 per cent of crop land (FOAG 2021). The Swiss wheat market is highly protected, i.e. there are quotas and high tariffs for wheat imports (Esposti and Listorti 2018). To establish prices within Switzerland, the national industry organization publishes producer reference prices, which are negotiated within the industry organization each year prior to the planting season.[2] These reference prices are not binding but a good indicator of average annual producer prices, i.e. prices vary only little between grain elevators and throughout the growing season, even in case of large amounts of downgraded wheat. Unlike in less protected markets (see e.g. Roberts et al. 2022), the prices also show very little volatility after a shock (see also Figure A3 in the online Appendix). There exist several price classes in which approved wheat varieties are allocated to, depending on the production type (e.g. nonorganic, organic, low- or no-pesticide production practices and labels), purpose of use (bread, biscuit or feed), quality potential, and general agronomic performance potential.[3] Swiss wheat producers use a spectrum of varieties from different price classes in practice (swiss granum 2020), also reflecting farm-specific wheat production conditions (Möhring and Finger 2022). Our analysis focuses on nonorganic wheat production (Möhring and Finger 2022). Wheat prices are highest for bread wheat varieties and these are subdivided into the price classes *Top* (highest price), *I* and *II* (lowest price for bread varieties). There is a single price class for biscuit wheat varieties with a price level similar to a bread variety in price class *II*. Varieties allocated to the price class feed wheat have the lowest price, i.e. approximately a third less than varieties in class *Top* and a quarter less than varieties in class *Biscuit* at 2019 price levels. Figure A3 in the online Appendix illustrates historical producer reference prices for each price class and shows the little price fluctuation between years.

Swiss wheat producers face little market price risks due to the high market protection (Esposti and Listorti 2018); however, varieties allocated to the bread and biscuit price classes are subject to a potential downgrading to the animal feed price class due a Hagberg Falling Number below 220 s (swiss granum 2022). More specifically, the Hagberg Falling Number is evaluated for each harvest delivery at grain elevators following Hagberg (1960). Note that blending harvests with different Hagberg Falling Numbers is usually not done because even small amounts of grain affected by a low Hagberg Falling Number can reduce the baking quality and is therefore considered as too risky (Steber 2017). Additionally, some grain elevators have small price rewards or deductions for the protein content (only for price class *Top*) and the test weight (also referred to as specific weight or hectoliter weight). These rewards and deductions, if there are any, do not change producer reference prices by more than 4 per cent and do not affect the decision whether a harvest delivery is downgraded to the animal feed price class (swiss granum 2022).

2.3 Agronomic background

The Hagberg Falling Number is the internationally standardized industry indicator for low baking quality, although its suitability has been debated in the scientific literature (Newberry et al. 2018; Cannon et al. 2022). More specifically, the Hagberg Falling Number measures the time in seconds it takes for a standardized stirrer to fall through a standardized mixture made of water and flour (Hagberg 1960). Bread made of winter wheat that scores a low Hagberg Falling Number can have discolored loaves of low volume, poor texture, and poor sliceability (Chamberlain et al. 1981; Olaerts et al. 2016) and is consequently not purchased by consumers. There are several weather-dependent causes for a low Hagberg Falling Number, including pre-harvest sprouting, late-maturity amylase, and retained pericarp amylase (Cannon et al. 2022), and these causes can occur simultaneously (Clarke et al. 2005).

Pre-harvest sprouting, which is the germination of wheat kernels in the spike of the plant prior to harvest, is the main cause for a low Hagberg Falling Number in temperate climates (Nielsen et al. 1984; Mares 1993; Lunn et al. 2002) and is reported as the major cause for low Hagberg Falling Number scores in Switzerland (Swiss granum 2021). Especially precipitation during the growth phases of grain development to harvest, i.e. a few weeks prior to harvest, can drastically reduce the Hagberg Falling Number (King and Wettstein-Knowles 2000; Biddulph et al. 2008; Mares and Mrva 2008; Barnard and Smith 2012). Moreover, precipitation can cause unfavorable harvest conditions resulting in delayed harvests, which increases the risk of a Hagberg Falling Number that is too low (Olaerts et al. 2016). Late-maturity amylase and retained pericarp amylase are associated with temperature shocks (Cannon et al. 2022), especially after exposure to hot temperatures close to harvest (Biddulph et al. 2008; Barnard and Smith 2012).

The occurrence of pre-harvest sprouting, late-maturity amylase, and retained pericarp amylase also strongly depend on the genetic composition of a wheat variety (Biddulph et al. 2007, 2008; Mares and Mrva 2008; Barnard and Smith 2012; Ji et al. 2018; Wang et al. 2020) and possibly other environmental factors (Mares and Mrva 2014). Especially pre-harvest sprouting can reduce the baking quality (Cannon et al. 2022), but the Hagberg Falling Number test, as applied in the industry and this study, cannot show whether pre-harvest sprouting, late-maturity amylase, and/or retained pericarp amylase is the cause of a low Hagberg Falling Number score.

3 Methods

We build on the economic and agronomic background presented in Section 2 to develop a model that estimates precipitation effects on the risk of a downgrading of bread and biscuit wheat to feed wheat due to a low Hagberg Falling Number (Section 3.1). Next, we simulate revenue reductions after such a downgrading to feed wheat that ultimately translates into lower profits (Section 3.2).

3.1 Estimation of precipitation effects

This study focuses on precipitation effects close to harvest on the risk of a downgrading due to a low Hagberg Falling Number because of the well observed effects of precipitation during this period in the literature (Biddulph et al. 2008; Mares and Mrva 2008) and in Swiss wheat production (swiss granum 2021), while controlling for possible temperature-related, genetical, and environmental effects (see Section 2.3 for our selection of model variables). More specifically, we use a linear probability model[4] with variety and location as fixed effects to estimate overall precipitation effects on the risk of a downgrading of bread and biscuit wheat to animal feed wheat due to a low Hagberg Falling Number (Equation (2)) and cluster standard errors to correct for heteroscedasticity. The variety fixed effects α_v absorb unobserved, variety-specific confounders (e.g. genetics (Cannon et al. 2022)) and the location fixed effects γ_i absorb unobserved, location-specific environmental confounders (e.g. soil texture (Mares and Mrva 2008)).

$$d_{vit} = \beta CP_{it} + \partial Z_{it} + \alpha_v + \gamma_i + \varepsilon_{ivt} \quad (2)$$

The binary dependent variable d_{ivt} shows whether bread or biscuit wheat from variety v harvested at location i in year t is downgraded to feed wheat due to a Hagberg Falling Number score below the Swiss industry's threshold of 220 s (1 = downgrading; 0 = no downgrading).[5] Our explanatory variable of interest is cumulative precipitation CP_{it} measured over a certain period prior to harvest, the control variables Z_{it} capture weather effects that may be correlated with cumulative precipitation close to harvest $CP_{it,}$ and the error term ε_{ivt} summarizes remaining effects. The parameters β and ∂ are estimated using the ordinary least squares estimator and standard errors are clustered by a 'region x year' variable to correct for heteroskedasticity in a linear probability model (details follow below). We are particularly interested in β, which shows the marginal effect of cumulative precipitation close to harvest CP_{it} on the risk of a downgrading.

We control for precipitation effects not captured in cumulative precipitation close to harvest CP_{it} and for nonlinear temperature effects using optimal degree-days and heat degree-days because these variables can also affect the Hagberg Falling Number and may be correlated with precipitation close to harvest CP_{it} (Biddulph et al. 2007; Barnard and Smith 2012). Optimal degree-days measure temperature loads[6] between 5°C and an upper heat threshold and heat degree-days measure temperature loads above this heat threshold (see e.g. D'Agostino and Schlenker 2016). The literature shows that especially weather conditions at the end of the growing season, i.e. during the growth phases of grain development to harvest, affect the Hagberg Falling Number (Mares 1993; Barnard and Smith 2012; Olaerts et al. 2016). Therefore, we split the growing season into two periods, in which we measure weather exposure. Period 2 is close to harvest and is used to measure our variable of interest cumulative precipitation CP_{it} and the control variables optimal degree-days and heat degree-days close to harvest. Period 1 lasts from planting to the beginning of period 2 and controls for cumulative precipitation, optimal degree-days and heat degree-days outside of period 2. Consequently, the control variables Z_{it} consist of cumulative precipitation in period 1 and optimal degree-days as well as heat degree-days in period 2 and period 1 (in total five weather control variables in addition to the variety and site fixed effects).

The model requires the definition of a specific day that splits the growing season into period 1 and period 2, and we also need to define a heat threshold to differentiate between optimal degree-days and heat degree-days. The agronomic literature does not indicate clear definitions of both parameters in the context of a downgrading due to a low Hagberg Falling Number. Thus, we run a data-driven grid search and estimate Equation (2) for each combination of the two parameters (the number of days prior to harvest for the split into the two periods as well as the heat threshold for the differentiation between optimal degree-days and heat degree-days[7]) and use the parameter combination for which the model has the largest goodness of fit, i.e. the lowest residual sum of squares. Note that these two parameters are constant across locations and years; however, the exact dates for period 2 and period 1 are location- and year-specific because of location- and year-specific planting and harvest dates. We verify this data-driven derivation of these two parameters by running robustness checks that use previously applied weather measurement periods and other heat thresholds (see Section 5.3 for details).

Identification strategy

There are several reasons why the model described above is suitable to identify precipitation effects on the risk of a downgrading due to a low Hagberg Falling Number. Firstly, it is a reduced-form model that only uses exogenous weather measurements as independent variables, i.e. downgrading events do not affect weather exposure. Secondly, we select model variables based on previous findings (see Section 2.3) and minimize omitted variable bias by controlling for a myriad of potential confounders that may be correlated with cumulative precipitation in period 2 CP_{it} and affect the risk of a downgrading due to a low Hagberg

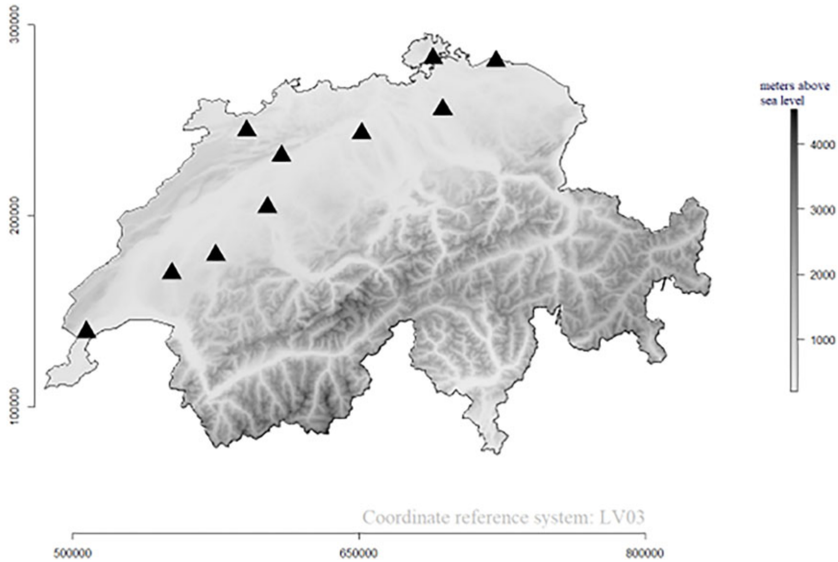


Figure 1. Locations of varietal field trials.

Falling Number. More specifically, we control for observed nonlinear temperature effects using optimal degree-days and heat degree-days in period 2 (close to harvest) and period 1 (from planting to the beginning of period 2). We also control for observed precipitation effects in period 1. In addition, we control many unobserved confounders by using variety and location fixed effects. Thirdly, the model implicitly accounts for potential adaptations in management as a response to weather risk exposure (e.g. adjusting harvest dates, including a harvest before full physiological ripeness with successive post-harvest drying in case of forecasted prolonged precipitation; see also Section 4.1). Fourthly, a linear probability model offers a clear interpretation of coefficients and avoids the incidental parameter problem that may cause biased estimates in the presence of variety and location fixed effects in generalized linear models such as logit or probit regression (Lancaster 2000; Angrist and Pischke 2009; Breen et al. 2018). Yet, we use generalized linear models as robustness checks to compare sign and significance of estimated weather effects in the linear probability model (see Section 5.3).

The use of field trial data supports the identification of pure precipitation effects on the risk of a downgrading due to a low Hagberg Falling Number because field management is standardized, i.e. potentially confounding changes in input or output prices do not change field management and exposure to production risks (e.g. droughts) does not cause a deviation from best management practices. Moreover, field trial data reduce the challenge of measurement errors in the weather variables that might bias our estimates (Auffhammer et al. 2013) because we know exact field locations that we match with high-quality weather data. More specifically, we use homogenized and quality-checked gridded weather data provided by experts in climatology and meteorology (Frei 2014). Measurement errors in the binary dependent variable (1 = downgrading; 0 = no downgrading), if there are any, are unlikely to correlate with weather exposure and thus unlikely to bias our estimates (Hausman 2001).

Error terms in linear probability models are heteroskedastic and we expect them to be spatially autocorrelated. Therefore, we use a ‘region times year’ variable to cluster standard errors. More specifically, we allocate 5 locations to the west and 5 locations to the east region because the 10 experimental sites are placed along a west-east gradient (see Fig. 1).

This results in 24 clusters (2 regions times 12 years)[8] that account for spatial autocorrelation within a region.

3.2 Simulation of profit reductions

To assess the economic relevance of the identified effects, we simulate revenue reductions due to a downgrading to feed wheat caused by a low Hagberg Falling Number by following Equation (3). The revenue reduction after such a downgrading of variety v harvested at location i in year t is denoted as $\Delta\pi_{vit}$. A downgrading to feed wheat reduces the producer price Δp_{vt} by the year-specific difference between the price of the price class the variety is allocated to (i.e. *Top*, *I*, *II*, *Biscuit*) and the price of feed wheat. The yield quantity of variety v harvested at location i in year t is denoted as y_{vit}.

$$\Delta\pi_{vit} = \Delta p_{vt} * y_{vit} \tag{3}$$

These revenue reductions directly translate into lower profits and farm income because the major weather risk exposure is close to harvest, i.e. after all field inputs have been applied and thus no changes in costs occur.

4 Data

We combine agronomic data (described in Section 4.1) with gridded weather data (described in Section 4.2) to estimate precipitation effects on the risk of a downgrading due to a Hagberg Falling Number below 220 s. For the simulation of revenue reductions after such a downgrading, we combine agronomic data with price data (described in Section 4.3).

4.1 Agronomic data

We use a panel dataset from the official Swiss wheat varieties trial network provided by Agroscope (the Swiss Confederation's center of excellence for agricultural research) and swiss granum (Swiss industry organization for cereals, oilseeds, and protein crops)[9] that consists of 1,859 bread and biscuit winter wheat observations of commercially available varieties measured at 10 sites between 2008 and 2019. The wheat varieties trial network aims to evaluate the performance of established and new wheat varieties under conventional rain-fed agriculture at the 10 representative sites shown in Fig. 1. Site locations reflect the heterogeneity in agri-environmental conditions in Swiss winter wheat production and are in vicinity to major winter wheat production regions, i.e. in the lowlands as shown in Fig. 1.

The portfolio of commercially available varieties is the same at each location in a given year so that spatial variability in production conditions is reflected. The portfolio composition (i.e. varieties considered) varies between years, giving due consideration to the introduction and recommendation of new winter wheat varieties. While the portfolio composition changes over time, each commercially available variety is part of the panel for several years to reflect temporal variability of weather conditions. In our analysis, we follow Swiss market conditions and assume that bread and biscuit wheat is downgraded to feed wheat if observing a Hagberg Falling Number below 220 s. The Hagberg Falling Number was assessed in the field trial network's laboratory for each harvested plot, which have a size between 6.5 and 10.2 m^2. We refer to Herrera et al. (2018, 2020) for more details regarding the setup of the field trial network. Table 1 provides sample statistics including the number of downgrading events and Figure A1 in the online Appendix shows historical distributions of Hagberg Falling Numbers and of crop yield quantities.

Management in the varieties trial network is standardized and follows the recommended best management practice for conventional (i.e. nonorganic) winter wheat production in

Table 1. Overview of downgrading events, 2008–2019.

Price class	Bread wheat			Biscuit wheat	Total
	Top	I	II		
Observations	697	652	377	105	1,859
Number of varieties	13	12	11	2	38
Downgrading events	30	26	22	8	86
Share of downgraded observations	4.30%	3.99%	5.84%	7.62%	4.63%

Note: Bread and biscuit wheat with a Hagberg Falling Number below 220 s is downgraded to feed wheat.

Switzerland. More specifically, planting (around mid-October) and harvest (between July and August in the consecutive year) takes place under favorable weather conditions, the amount of nitrogen fertilizer is up to 175 kg per hectare, and pesticides are applied if necessary. Planting and harvest dates differ between site and year (see also Figure A2 in the online Appendix) but are the same for all varieties at a certain site and year. In the varietal trial network, there is no response in management decisions to changes in input or output prices and production risks do not cause a deviation from best management practices. Wheat can be harvested a few days before full physiological ripeness and post-harvest dried to prevent weather risk exposure that may affect the Hagberg Falling Number (Donaldson 1968). In case of such an early harvest at a specific site, all varieties are still harvested on the same day at the affected site. An early harvest as a response to forecasted unfavorable weather conditions is also observed in practice[10] and implicitly accounted for in our model (see Section 3.1). We refer to Herrera et al. (2018, 2020) for more details regarding the field management in the Swiss wheat varieties trial network.

The here used dataset is representative for Swiss winter wheat production using conventional management (i.e. based on the use of pesticides) that follows the recommended best management practices also applied in this field trial. While there is heterogeneity in Swiss wheat production management, e.g. organic as well as low- and no-pesticide production (e.g. Möhring and Finger 2022), the conventional production used in the field trial is representative, especially with respect to climate risk exposure. More specifically, most wheat producers operate under similar management practices as applied in the field trial, including a harvest before full physiological ripeness and use of the same varieties (swiss granum 2020). Moreover, all field inputs are applied before the risk period close to harvest commences, i.e. field inputs cannot be adjusted close to harvest. A difference between management of field trials and practice is the field size, but field trial data can still provide useful insights in case data from practice is not available (Lobell et al. 2011b).

4.2 Weather data

We derive site-specific daily precipitation amounts, daily minimum temperature, and daily maximum temperature from homogenized and quality-checked gridded datasets (spatial resolution of 1×1 km) provided by the Federal Office of Meteorology and Climatology (Frei 2014). Each grid in the dataset contains weather variables based on several surrounding weather stations, whose daily weather measurements are quality checked and removed if they are of low quality (e.g. due to technical failure of measurement instruments) and interpolation particularly takes into account Swiss topography and microclimates. Thus, this homogenized dataset provided by experts is of highest accuracy and does not contain missing values that bias the estimation of weather effects (Auffhammer et al. 2013).[11] Weather measurements differ between sites and years but are equal for varieties grown at the same site and year.

Table 2. Overview of weather data, 2008–2019.

		min	mean	median	max	Sd
Period 2	Precipitation	15.92	101.45	102.30	242.07	49.90
	Optimal DD	2,046	2,359	2,370	2,660	126.20
	Heat DD	0	43	26	153	37.90
Period 1	Precipitation	399.3	663.8	631.7	1,094	140.56
	Optimal DD	4,506	5,656	5,626	6,893	525.35
	Heat DD	0	13	11	55	10.57

Note: Period 2 considers weather exposure 31 days prior to harvest and period 1 from planting to the beginning of period 2. Precipitation is measured in millimeters and both forms of degree-days are temperature loads based on measurements in°C. The temperature threshold to differentiate between optimal- and heat degree-days is at 27°C and was derived with the numerical method explained in Section 3.1 so that optimal degree-days measure temperature loads between 5°C and 27°C and heat degree-days measure temperature loads above 27°C (see also section Results). DD is degree-days and sd standard deviation.

We use daily minimum and maximum temperatures to calculate the control variables optimal degree-days and heat degree-days (see Section 3.1). More specifically, we follow previous research (e.g. Tack et al. 2015; Gammans et al. 2017; Ortiz-Bobea et al. 2018; Bucheli et al. 2022) and estimate daily temperature curves[12] to consider intraday temperature variation, which is essential in estimating weather effects in crop production (Lobell 2007). Subsequently, we derive the daily temperature load for optimal degree-days and heat degree-days by calculating the corresponding areas below the estimated temperature curves (see Snyder (1985) and D'Agostino and Schlenker (2016) for illustrations). Finally, we aggregate the daily temperature loads of optimal degree-days and heat degree-days to derive accumulated optimal degree-days and heat degree-days as shown in Equation (2). Table 2 provides summary statistics of the weather data measured at the 10 locations.

4.3 Price data

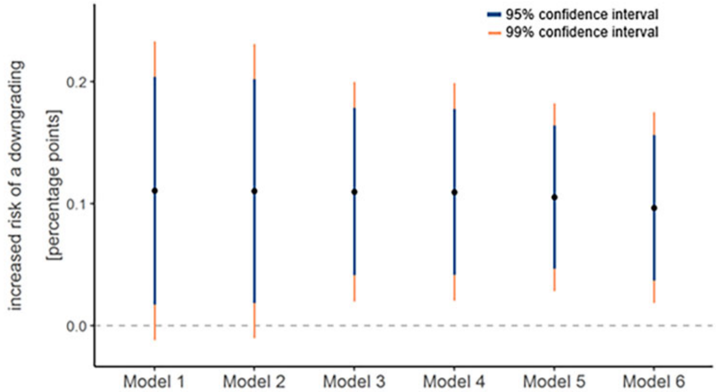
The Swiss industry organization for cereals, oilseeds, and protein crops (swiss granum) publishes agreed producer reference prices for each price class (i.e. *Top, I, II, Biscuit, Feed*) alongside a list of commercially available wheat varieties that also indicates the price class to which a variety is allocated to.[13] These producer reference prices are a good indicator of realized producer prices (see Section 2.2). As shown in Figure A3 in the online Appendix, producer reference prices did not change between 2014 and 2019 (last year in our panel) and show very little volatility prior to 2014. All prices are in Swiss francs per 100 kg (Swiss francs/100 kg).

5 Results

To begin this section, we show the estimated precipitation effects on the risk of a downgrading based on Equation (2). After that, we illustrate the economic relevance of a downgrading based on the simulation of revenue reductions following Equation (3). Further, we present a summary of robustness checks that are discussed in detail in Section A3 of the online appendix.

5.1 Estimated precipitation effects on the risk of a downgrading

Fig. 2 shows coefficient plots for the estimated marginal effects of cumulative precipitation close to harvest (period 2), denoted as β in Equation (2), on the risk of a downgrading of bread and biscuit wheat to animal feed wheat due to a Hagberg Falling Number below 220 s. A black point marks the point estimate of the estimated β and a vertical line in blue (orange) illustrates the 95 per cent (99 per cent) confidence interval. An effect is significant at the 5 per cent (1 per cent) level, if the 95 per cent (99 per cent) confidence interval in



		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Period 2 (close to harvest)	Optimal degree-days	■	■				
	Heat degree-days	■	■				
Period 1 (planting – period 2)	Precipitation	■		■			
	Optimal degree-days	■	■				
	Heat degree-days	■	■				
Fixed effects	Location	■	■	■	■		
	Variety	■	■	■	■	■	
Parameter definitions	Season split [days prior to harvest]	31	31	31	31	31	31
	Heat threshold [°C]	27	27	-	-	-	-
Goodness of fit	Adj. R-squared [%]	15.03	15.07	11.63	11.30	10.11	5.31

Figure 2. Estimated cumulative precipitation effects close to harvest on the risk of a downgrading.
Note: In the upper part, black points show the average marginal precipitation effect in period 2 (our main variable of interest and denoted as β in Equation 2), the vertical blue lines mark 95 per cent confidence intervals and vertical orange lines marks 99 per cent confidence intervals. Model 1 (first column) is our main specification in which control variables (optimal- and heat degree-days in period 1 and period 2, precipitation in period 1) and choice of fixed effects (location and variety) are based on agronomic findings. Selected control variables and fixed effects of a specific model are marked with a black square in the table. In models 2–6, we remove control variables to show the sensitivity of our estimated marginal average precipitation effect in period 2 on the risk of a downgrading. Model 2 excludes precipitation in period 1, Model 3 the temperature variables, Model 4 excludes all weather control variables, Model 5 only considers the variety fix effects, and Model 6 has no control variables and fixed effects. Parameter definitions (season split and heat threshold) are derived for each model with a grid search. The days prior to harvest show where the growing season is split into period 1 and period 2 and the heat threshold is used to differentiate between optimal degree-days and heat degree-days.

blue (orange) is above the dashed horizontal line. Model 1 is our main specification because its selection of control variables is based on previous findings in the literature (see Sections 2.3 and 3.1). We then remove control variables and fixed effects in Models 2–6 to show the sensitivity of the estimated marginal effects of cumulative precipitation close to harvest (period 2).

For Model 1, our data-driven split of the growing season into period 2 (close to harvest) and period 1 (from planting to the start of period 2) is at 31 days prior to harvest (see Section 3.1 for details on the data-driven split of the growing season). This split is highly plausible from an agronomic point of view because weather conditions close to harvest have the largest impact on the Hagberg Falling Number (Mares 1993; Barnard and Smith 2012; Olaerts et al. 2016). Thus, we estimate an increased risk of a downgrading due to a Hagberg Falling Number below 220 s of ca. 0.1 percentage points for each millimeter of precipitation

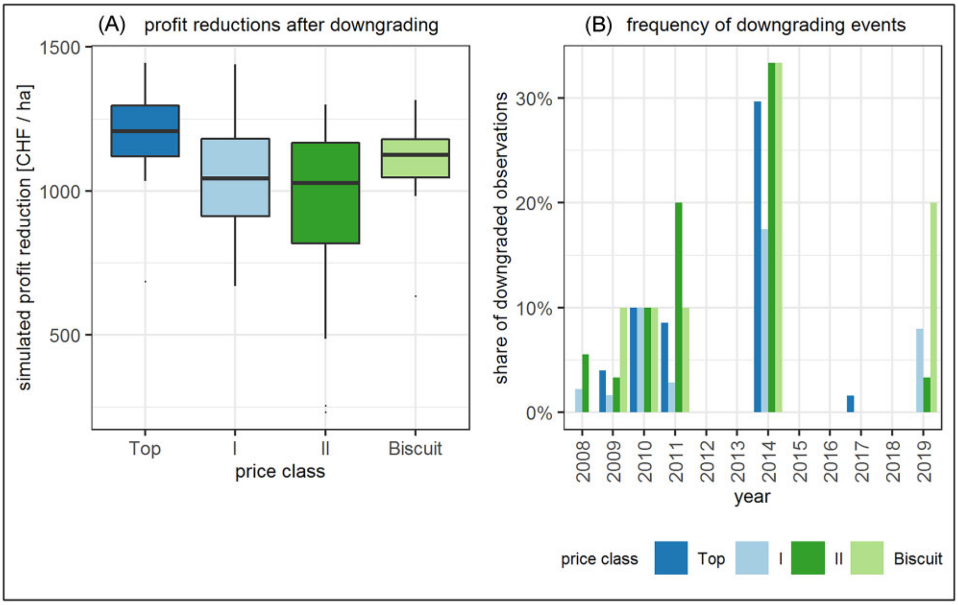


Figure 3. Profit reductions after a downgrading (a) and frequency of downgrading events (b).
Note: Price classes *Top*, *I* and *II* are bread wheat. Subpanel (a) on the left shows simulated profit reductions with a boxplot for each price class. A box shows the interquartile range from the 25th percentile to the 75th percentile. The bold line within a box represents the median. *CHF/ha* means Swiss francs per hectare.

during the 31 days prior to harvest (=period 2). This estimated effect is significant at the 5 per cent significance level (the 95 per cent confidence interval in blue is above the horizontal dashed line).

To illustrate the effect of cumulative precipitation aggregated over the 31 days prior to harvest at the 10 field trial sites, we multiply the site- and year-specific observed precipitation amounts with the estimated marginal effect. This shows that cumulative precipitation aggregated over the 31 days prior to harvest has increased the risk of a Hagberg Falling Number below 220 s, i.e. the risk of a downgrading, between 1.76 percentage points (dry summer of 2015) and 26.74 percentage points (wet summer of 2014, which also caused many downgrading events in practice (swiss granum, 2021). See Section A2 of the online Appendix for more details.

The omission of control variables and fixed effects (Models 2–6) from our main model (Model 1) reveals only little sensitivity of the point estimates for cumulative precipitation in period 2 and confidence intervals become narrower with the omission of the weather variable controls, indicating multicollinearity between cumulative precipitation in period 2 and the weather variable controls (Fig. 2). Moreover, the split of the growing season into period 2 (close to harvest) and period 1 (from planting to the beginning of period 2) remains constant at 31 days prior to harvest. A comparison of the goodness of fit between Model 5 and Model 6 shows a strong effect of the variety on the risk of a Hagberg Falling Number below 220 s. Model outputs are presented in Section A2 of the online Appendix.

5.2 Economic relevance of a downgrading

The left subpanel in Fig. 3 shows simulated profit reductions after a downgrading due to a Hagberg Falling Number below 220 s and per price class (see Section 2.2 for more information about price classes), which we derive using Equation (3). The right subpanel shows

Table 3. Expected profit reduction, 2008–2019.

	Top	I	II	Biscuit	All
Expected profit reduction in CHF/ha	54.02	44.39	56.41	86.13	52.15

Note: All is the expected profit reduction of all observations. *CHF/ha* is Swiss francs per hectare.

the frequency of downgrading events due to a Hagberg Falling Number below 220 s per year and price class.

Both subpanels reveal that all price classes can be affected by a downgrading to feed wheat. A downgrading due to Hagberg Falling Number below 220 s causes large profit reductions (left subpanel) and is therefore of highest economic relevance. The largest simulated profit reduction is 1,445 Swiss franc per hectare (representing ca. 40 per cent of the total expected revenue) and from a variety belonging to the price class *Top* (highest price but usually lower yields compared to varieties in other price classes). Median profit reductions are also largest for the price class *Top*, followed by *Biscuit* (low price but comparatively high yields), *I* and *II*. Precipitation during the growth phases relevant for the risk of a downgrading barely affects crop yield quantity (Barnabás et al. 2008; Farooq et al. 2014; Varga et al. 2015) so that a possible natural hedge between a downgrading event and yield quantity, if there is any, would change the result only minimally. The subpanel on the right in Fig. 3 (see also Table 1) shows that downgrading events due to a Hagberg Falling Number below 220 s are rare and occur irregularly. More specifically, the risk of such a downgrading can be idiosyncratic (downgrading of few observations within a location) or systemic (downgrading of many observations within and across locations) within a year. As shown in Fig. 3b, a large share of observations was downgraded in 2014 (systemic risk), which was also observed in practice (swiss granum 2021), whereas only few downgrading events occurred in 2008 and 2009 (idiosyncratic risk). There are also years (2012, 2013, 2015, 2016, and 2018) without a single downgrading in our dataset as shown in Fig. 3b. Table 3 shows the expected loss in revenues for each price class to provide a measure that jointly reflects the economic severity and frequency of downgrading events.

5.3 Summary of robustness checks

Several robustness checks confirm the significant effect of cumulative precipitation close to harvest on the risk of a downgrading due to a Hagberg Falling Number below 220 s. This section summarizes these robustness checks that are presented in detail in Section A3 of the online Appendix.

First, our main model specification (Model 1 in Fig. 2) might have an omitted variable bias, i.e. there might be other variables that are correlated with cumulative precipitation in period 2 (close to harvest) and affect the risk of a downgrading (e.g. cold temperatures, time trend). To begin, we add freezing degree-days (temperature load below 0°C) as another weather control[14] because temperatures below 0°C might also affect the Hagberg Falling Number (Craven et al. 2007). We find that freezing degree-days have no effect on the risk of a downgrading due to a Hagberg Falling Number below 220 s and do not change the estimated cumulative precipitation effect in period 2. Next, we add a linear time trend and find that this trend has no significant effect on the risk of a downgrading due to a Hagberg Falling Number below 220 s and does not change the estimated cumulative precipitation effect in period 2. A quadratic time trend provides the same findings. See Section A3.1 of the online Appendix.

Second, our main model specification (Model 1 in Fig. 2) assumes a linear cumulative precipitation effect on the risk of a downgrading. We verify this assumption with a model specification that allows a nonlinear cumulative precipitation effect in period 2 within a linear probability model. The result shows that the use of a linear cumulative precipitation effect, as used in our main specification, is appropriate. See Section A3.2 of the online Appendix.

Third, period 1 in our main specification aggregates weather effects from planting to the beginning of period 2. This long period might cause an aggregation bias and hide some relevant precipitation effects. Therefore, we split period 1 into two subperiods using different split criteria. Splitting period 1 does not affect the estimated cumulative precipitation effect in period 2 and only precipitation effects 3 days after the end of period 2 have a significant effect on the risk of a downgrading. This shows that our main specification captures most relevant precipitation effects and indicates that precipitation amounts earlier in the year have no effect on the risk of a downgrading due to a Hagberg Falling Number below 220 s. This is also in line with the agronomic literature (Mares 1993; Barnard and Smith 2012; Olaerts et al. 2016). See Section A3.3 of the online Appendix.

Fourth, in our main specification presented above we use a linear probability model because of the clearer interpretation of coefficients and the limitations associated with generalized linear models in the presence of fixed effects (see also Angrist and Pischke 2009 and Breen et al. 2018, who show the advantages of using a linear probability model). Yet, in a robustness check, we verify sign and significance of estimated cumulative precipitation effects in period 2 using logit, probit, and Poisson regression models. These models confirm the positive and significant cumulative precipitation effect in period 2 on the risk of a downgrading due to a Hagberg Falling Number below 220 s. See Section A3.4 of the online Appendix.

Fifth, we run grid searches using the maximum number of correctly predicted downgrading events instead of the minimum residual sum of squares used in our main specification to define the model parameters (split of growing season, heat threshold). This results in equal or similar parameter definitions, and very similar estimated effects of cumulative precipitation in period 2 compared to our main model (Model 1 in Fig. 2). As an alternative to the data-driven grid search, we define the split of the growing season at 10 and 20 days prior to harvest (similar to the weather risk exposure measured in Barnard and Smith (2012)) and additionally consider a split 40 days prior to harvest. Estimated cumulative precipitation effects for a period 2 lasting from harvest until 10, 20, and 40 days prior to harvest are very similar to the estimated effect in our main specification in which period 2 lasts from harvest to 31 days prior to harvest. In line with the third robustness check, a split too far away from harvest results in nonsignificant precipitation effects in period 2 and indicates that precipitation amounts too far from harvest have no effect on the risk of a downgrading. Additionally, we change the heat threshold, used to differentiate between optimal- and heat degree-days), and find no effect on the estimated precipitation effects in period 2. See Section A3.5 of the online Appendix.

Finally, we run our main specification (Model 1 in Fig. 2) without data from the catastrophic year 2014 to exclude that our finding solely results from the observations made in this year. Using this subsample, we still find significant cumulative precipitation effects close to harvest. See Section A3.6 of the online Appendix.

6 Discussion

This section addresses the external validity of our results and then summarizes the challenges involved in the management of the risk of a downgrading due to a low Hagberg Falling Number at farm level.

Our results based on Swiss field trial data are representative for conventional Swiss wheat producers (see Section 4.1) and we expect our findings to be transferable to other wheat markets but that the magnitude of precipitation effects on the risk of a downgrading and the economic relevance of a downgrading vary due to different production conditions (e.g. weather exposure, varieties, management) and different market conditions (e.g. level of market protection, different and more volatile wheat prices, different thresholds for the Hagberg Falling Number).

Managing the risk of a downgrading due to a low Hagberg Falling Number at farm level is not straightforward, involves trade-offs, and faces limits. At the beginning of the growing season, the choice of the variety is an important factor affecting the risk of such a downgrading (e.g. Biddulph et al. 2008; Mares and Mrva 2008; Barnard and Smith 2012; Ji et al. 2018). However, there are trade-offs between a variety's vulnerability to the causes of a low Hagberg Falling Number (see Section 2.3) and other characteristic such as the yield potential.[15] Current breeding efforts have the potential to minimize these trade-offs (e.g. DePauw et al. 2012; Mares and Mrva 2014) and our findings underline the relevance of considering the risk of a downgrading due to a low Hagberg Falling Number in breeding programs, especially for varieties used in regions with increasing heavy precipitation events close to harvest as it is the case in Switzerland (Scherrer et al. 2016). During the growing season, there are no options to reduce the risk of a downgrading due to a low Hagberg Falling Number with field inputs because the major risk exposure occurs after all field inputs have been applied.

Harvest should be completed as soon as possible because the risk of a downgrading increases with a delayed harvest (Olaerts et al. 2016). A large harvest capacity can therefore reduce the risk of a downgrading (Donaldson 1968). Farmers can increase their harvest capacity by using more combines and infrastructure for post-harvest drying because this allows a harvest a few days prior to full physiological ripeness. However, increasing the number of combines and using post-harvest drying infrastructure increases production costs and fails to reduce the risk of a downgrading during prolonged unfavorable weather conditions (Donaldson 1968; Davis and Patrick 2002). In addition to these on-farm management options, insurance solutions that cover the risk of a downgrading due to a low Hagberg Falling Number can buffer the resulting financial losses and are offered to Swiss winter wheat producers.[16] Whether the use of more combines, post-harvest drying infrastructure and insurance solutions reduces the financial risk of a downgrading due to a low Hagberg Falling Number cannot be answered with the dataset applied in this study but opens an interesting line for future research.

7 Conclusion

This paper estimates precipitation effects on the risk of a downgrading of bread and biscuit wheat to animal feed wheat due to a low Hagberg Falling Number and simulates profit reductions that result from such a downgrading. Using data from the Swiss winter wheat field trial network, we find cumulative precipitation aggregated over the 31 days prior to harvest to increase the risk of a downgrading on average by 0.1 percentage points for each millimeter of precipitation. We estimate an expected loss of 52 Swiss francs per hectare across all observations. In specific years, however, downgrading can result in large economic losses of up to 1,445 Swiss francs per hectare (representing ca. 40 per cent of the total expected revenue). This highlights the need to consider weather-dependent crop quality in economic risk assessments, informs various actors in food systems about the underlying risk exposure, and provides a basis for improved risk management.

Wheat producers should consider the risk of a downgrading due to a low Hagberg Falling Number in their risk management strategy as they bear large potential financial losses. Managing the risk of a downgrading at farm level is not simple and involves many trade-offs. Especially variety choice and the breeding of varieties that are more robust to the causes of a low Hagberg Falling Number have the potential to improve risk management. Thus, the risk of a downgrading due to a low Hagberg Falling Number also affects actors associated with input supply such as wheat breeders, seed distributors, and extension services.

Moreover, it also affects the supply chain management of downstream actors (e.g. millers, retailers), particularly after large-scale downgrading events in protected markets.

Agricultural policy could consider the effects of weather-dependent crop quality on the financial well-being of farmers and not only consider crop yield quantity. Policymakers can support farmers' risk management by establishing a legal framework that incentivizes the breeding of improved varieties and the implementation of tools, such as insurance products, that reduce the risk of a downgrading due to a low Hagberg Falling Number. Moreover, policymakers can support data collection of yield quantity and quality, also from observations made in practice. These data can provide a valuable basis for improved risk assessments and improvements of risk management tools such as insurance solutions.

Future research should consider price-relevant yield quality characteristics in economic risk assessments, identify the drivers of yield quality, and develop improved and cost-efficient tools to manage downside risks resulting from low yield quality. Field research can provide a valuable basis for this and should continue to elucidate all environmental, managerial, and genetic factors influencing price-relevant yield quality characteristics. Future research should also estimate climate change effects on yield quality, also under the consideration of changes in the duration of growing and harvesting seasons and farmers adaptations. Furthermore, similar research in other markets than Switzerland and for other crops with price-relevant quality characteristics such as rice, canola, and horticultural products shall be conducted.

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Supplementary material

Supplementary data are available at *Q Open* online.

Data Availability Statement

The data that support the findings of this study are not publicly available but are available from Agroscope and MeteoSwiss. The R code of our analysis is available here https://github.com/AECP-ETHZ/Precipitation-causes-quality-losses-of-large-economic-relevance-in-wheat-production/blob/main/Code_WheatQuali.R.

Conflict of interest

The authors declare no conflict of interest.

End Notes

1 There is little chance that the risk of a downgrading affects production costs because risk exposure occurs towards the end of the growing season where usually no further crop management takes place.

2 The reference prices are published here: https://www.swissgranum.ch/zahlen/preise (only available in German or French and last accessed 05.01.2024).

3 The agronomic performance, comprising yield and resistance to diseases, and quality parameters are evaluated within the official Swiss wheat varieties trial network. Resistance to the risk of a downgrading plays a minor role for the allocation of a variety to a price class. More details can be found in

the list of recommended varieties published here: https://www.swissgranum.ch/richtlinien/sorten#c45 (only available in German or French and last accessed 05.01.2024). See e.g. Möhring and Finger (2022) for discussion on the Swiss wheat market.

4 Additionally, we run logit, probit, and Poisson regression models as robustness checks. They all confirm the findings of the linear probability model. See subsection 'Identification strategy' for reasons why the linear probability model is better for our research question and Section 5.3 for a summary of robustness checks.

5 We here estimate an average effect across all varieties while controlling for variety-specific effects. The dataset exploited here does not contain enough observations per variety to provide reliable variety-specific effects.

6 Temperature loads reflect by how much and for how long temperatures exceed a temperature threshold (D'Agostino and Schlenker 2016).

7 In the grid search, we consider a split of the growing season at 1–60 days prior to harvest following agronomic suggestions (see Section 2.3) and a split of optimal- and heat degree-days at 18–32°C.

8 We do not cluster by year because a small number of clusters (here 12 years) may result in too narrow standard errors. We verified our results by using 'location times year' clusters (10 locations times 12 years = 120 clusters). Using these 120 'location times year' clusters does not change our findings.

9 More information about the field trial sites of Agroscope can be found here: https://www.agroscope.admin.ch/agroscope/en/home/topics/plant-production/field-crops/crops/straw-cereals%20.html (last accessed 03.01.2024) and the website of Swiss granum can be accessed here: https://www.swissgranum.ch/(only available in German or French and last accessed 03.01.2024).

10 Farmers harvest before full physiological ripeness in practice, see e.g. https://www.agrarheute.com/pflanze/getreide/6-tipps-so-erkennen-landwirte-getreide-erntereif-608352 (only available in German and last accessed 03.01.2024).

11 Documentation that is more detailed can be found here: https://hyd.ifu.ethz.ch/research-data-models/meteoswiss.html (last accessed February 8, 2022).

12 These temperature curves are based on two sine curves. The first sine curve starts at the daily minimum temperature and goes to the daily maximum temperature. The second sine curve goes from the daily maximum temperature to the daily minimum temperature of the consecutive day. We approximate daily temperature curves because high resolution temperature data (e.g. hourly observations) is currently not available.

13 Current and historical producer reference prices can be found here: https://www.swissgranum.ch/zahlen/preise (last accessed 02.01.2024, only available in German and French). Current and historical wheat varieties commercially available in Switzerland can be found here: https://www.swissgranum.ch/richtlinien/sorten (last accessed 02.01.2024, only available in German and French).

14 We also considered hail events as another weather control variable and found hail not to affect the model output. However, only 32 out of 1,859 observations indicate a hail event so that the database of this robustness check is not of sufficient quality to be presented here.

15 Preferences for varieties are becoming more diverse in Switzerland (swiss granum 2020). However, many wheat producers preferred varieties with high yield potentials and high risk of a downgrading during the catastrophic year 2014. See e.g.: https://www.bauernzeitung.ch/artikel/landwirtschaft/grosse-auswuchsgefahr-beim-weizen-367022 (only available in German and last accessed 18.04.2022)

16 For instance, Swiss hail insurance offers a product that covers the financial losses after a downgrading: https://www.hagel.ch/de/versicherungen/ackerbau/(only available in German, French or Italian and last accessed 06.01.2024).

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