Precipitation causes quality losses of economic relevance in wheat production

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1. Introduction

Adverse weather conditions are among the most important production risks in crop production and climate change is amplifying these already existing weather risks (Lobell et al. 2011; 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 crop quality (Pereyra-Irujo and Aguirrezábal 2007; Lanning et al. 2011; Diacono et al. 2012). This puts food security and farmers' profitability at risk (Deschênes and Greenstone 2007; Haddad et al. 2016; Woli and Hoogenboom 2019). The assessment and management of weather-dependent quality risks is therefore essential to ensure food systems that provide high-quality foods for a growing population and is of interest to various actors including farmers, down- and upstream actors, crop breeders, crop insurance providers, researchers and policymakers. Yet, economic risk assessments of crop quality remain a largely unexplored research area because of limited data availability, and a particular lack of data availability from practice.

This article has two independent research objectives. Firstly, we estimate effects of adverse weather conditions on wheat quality. More specifically, we estimate overall precipitation effects on the risk of a downgrading of bread and biscuit wheat to animal feed wheat due to poor baking quality resulting from the activation undesired amylase proteins. Secondly, we assess the economic relevance of a downgrading risk from a farmer's perspective. 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 varieties from 2008 to 2019. Moreover, we discuss possible risk management options to cope with the weather-dependent downside risk of a downgrading in wheat production.

While there is a rich documentation of weather induced quality losses in various crops, only a few studies documented the economic relevance of these quality losses. For example, previous research highlighted weather-dependent quality effects on the economic performance of peanut production in the US (Ramsey et al. 2020), rice production in the US (Lyman et al. 2013; Nalley et al. 2016), rice production in Japan (Kawasaki and Uchida 2016) and of apple production in Switzerland (Dalhaus et al. 2020). A risk assessment of weather-dependent quality effects on the economic performance of wheat producers remains an open field of research, but research found adverse weather to activate undesired amylase proteins that cause poor baking quality that translates into economic losses in many wheat markets such as in the United States (Moore et al. 2017; Ji et al. 2018), Canada (Clarke et al. 2005; DePauw et al. 2012), Europe (Lunn et al. 2002), South Africa (Barnard and Smith 2012), Australia (Craven et al. 2007; Biddulph et al. 2008) and China (Wang et al. 2020). Especially the weather-dependent activation of undesired amylase proteins in grains has been found to be an economically important risk because even small amounts of amylase proteins can cause a complete loss of baking quality so that affected bread and biscuit wheat is downgraded to feed wheat and marketed at a much lower price (Mares and Mrva 2012).

This article fills an important literature gap by presenting an economic risk assessment from a farmer's perspective of weather-dependent wheat quality, and in particular of poor baking quality due to critical activity of undesired amylase proteins. Thereby, we provide three major contributions to the existing literature. Firstly, this article highlights the importance of weather-dependent wheat quality in economic risk assessments. Secondly, the results inform farmers, down- and upstream actors, extension services, insurers, crop breeders, researchers and policymakers about the underlying risk exposure. Thirdly, the results provide a basis to improve risk management and to guide breeding programs and the development of insurance solutions.

Wheat is among the most widely grown crops in the world and a downgrading due to active amylase proteins cause annual losses of more than one billion U.S. dollars at the global scale (Bewley et al. 2006; Shao et al. 2018). Here we focus on winter wheat production in the highly protected Swiss market because the mechanism in which a downgrading affects producer prices is representative for many other wheat markets, market price risks are almost absent and allow a clear focus on production risks, and winter wheat production as well as the risk of a downgrading are of highest relevance in Swiss crop production. More specifically, a downgrading of bread and biscuit wheat to animal feed wheat abruptly reduces producer prices and the resulting financial losses are borne by the affected farmers themselves. Systemic downgrading events occurred in approximately 25% of harvested bread and biscuit wheat in 2014 and 2021 and thus resulted in substantial economic losses for farmers, i.e. wheat revenues were reduced by up to 30% because of price reductions (swiss granum, 2021).

This article provides three key results. Firstly, precipitation effects of up to a month prior to harvest increase the risk of a downgrading of bread and biscuit wheat to animal feed wheat. More specifically, we estimate that an additional millimeter of precipitation within the month prior to harvest increases the risk of a downgrading by approximately 0.1 percentage points. Secondly, a downgrading to feed wheat causes large economic losses for farmers. We estimate historical profit reductions of up to 1'445 Swiss francs per hectare ($633 per acre). Thirdly, downgrading events occur rarely and not on a regular basis. The risk of a downgrading can be of idiosyncratic or systemic nature. We estimate an expected loss of 52 Swiss francs per hectare ($23 per acre) across all observations.

We derive these results using field trial data with detailed records on variety-specific yield quantity and quality measured at known locations. To minimize endogeneity, we match the exact field location with homogenized and quality-checked weather data and control for many potential confounders. Moreover, the use of trial data supports the identification of precipitation effects on the risk of a downgrading because changes in input or output prices do not change management practices at experimental sites. Finally, the activation of undesired amylase proteins that cause the downgrading occurs towards the end of the growing season and after all inputs have been applied. Thus, short-term adaptation responses to risk exposure do not differ between experiments and practice in the case of such a downgrading.

2. Background

This section shows how crop quality affects farmers' profits through producer prices, presents the Swiss wheat market and provides an agronomic background about weather effects on the activation of undesired amylase proteins, whose presence drastically reduces baking quality of bread and biscuit wheat.

2.1 Economic background

Crop quality is an important determinant of producer prices ultimately affecting profits. This 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}.

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

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) and is multiplied by the crop yield quantity y_{it}. 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. 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 article, bread and biscuit wheat of poor baking quality due to critical activity of undesired amylase proteins is downgraded to animal feed wheat. This causes an abrupt price reduction Δp_{it} and ultimately a profit reduction $\Delta \pi_{it}$. We assume production costs to be independent of a downgrading because the decision to downgrade is made at grain elevators and amylase activity, which is the cause of poor baking quality, emerges towards the end of the growing season after all inputs on the field have been applied (see section agronomic background). Critical activity of amylase proteins is a downside risk, i.e. there is no price reward for the absence of amylase proteins.

2.2 The Swiss wheat market

Wheat is the most important crop in Switzerland and covers approximately 50% 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. 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[1]. There exist several price classes in which approved wheat varieties are allocated to, depending on their purpose of use (bread, biscuit or feed), quality potential and general agronomic performance potential[2]. Bread wheat varieties realize the largest prices and are subdivided into the price classes *Top* (largest 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 (approximately a third less than varieties in class *Top* and a quarter less than varieties in class *Biscuit* at 2019 price levels). Figure AX in the online appendix illustrates historical producer reference prices that show little fluctuations between years.

Swiss wheat producers face little market price risks, however, varieties allocated to the bread and biscuit price classes are subject to a potential downgrading to the animal feed price class due to a critical activity of amylase proteins that cause a loss of baking quality. As described in section 2.1 Economic background, this downgrading abruptly reduces producer prices (e.g. by approximately a third for varieties allocated to price class *Top*) and is the economically most important quality risk for

[1] For instance, the Swiss cereal production organization reported selected realized producer prices for Top wheat between 48 CHF/dt - 54 CHF/dt in 2014, between 47.50 CHF/dt - 55 CHF/dt in 2015, between 49.50 CHF/dt - 54.50 CHF/dt in 2016, between 48 CHF/dt - 53 CHF/dt in 2017, between 47 CHF/dt - 52.50 CHF/dt in 2018, and between 47 CHF/dt - 51.50 CHF/dt in 2019. The reference price in each year was 52 CHF/dt. Reports are available in German, French and Italian: http://www.sgpv.ch/marktbericht (last accessed February 15, 2022).

[2] The agronomic performance, comprising yield and resistance to diseases, and quality parameters are evaluated within the official Swiss wheat varieties trial network. Resistance to amylase activity plays a minor role for the allocation of a variety to a price class.

bread and biscuit wheat producers in Switzerland[3]. The standard industry measure for poor baking quality due to amylase proteins is the Hagberg Falling Number (Hagberg 1960) and each harvest delivery is tested at grain elevators so that farmers are the ultimate recipient of price reductions. A Hagberg Falling Number below 220 seconds[4] results in a downgrading to feed wheat. Swiss wheat producers use a spectrum of varieties from different price classes in practice (swiss granum, 2020). This indicates that the producer reference price is not the only determinant of variety choice.

2.3 Agronomic background

Poor baking quality due to active amylase proteins is the most important quality risk affecting producer prices in Switzerland. Even small amounts of amylase proteins cause discolored loaves of low volume, poor texture and poor sliceability (Chamberlaint et al. 1981; Olaerts et al. 2016). Figure 1 illustrates how amylase proteins affect the baking quality of bread.

[insert figure 1 and check for copyrights]

Figure 1: Loss of baking quality due to critical amylase activity

The activation of amylase proteins, usually measured with the Hagberg Falling Number, is complex and yet not fully understood. Key determinants of amylase activity are weather conditions, wheat variety, durations of growing seasons and possibly other but yet unknown environmental factors and the interactions of these variables (Lunn et al. 2002; Biddulph et al. 2008; Mares and Mrva 2014; Olaerts et al. 2016). Although these determinants often interact with each other, a single determinant such as a genetic defect in a variety can also activate amylase proteins (Mares and Mrva 2008). Precipitation a few weeks prior to harvest is the most important weather variable affecting amylase activity and temperatures a few weeks prior to harvest might also have an effect (Mares 1993; Barnard and Smith 2012; Olaerts et al. 2016).

Precipitation a few weeks prior to harvest has well-documented effects on the activation of undesired amylase proteins and research has identified two major mechanisms. Firstly, precipitation a few weeks prior to harvest can cause pre-harvest sprouting, which is the germination of wheat kernels in the ear of the parent plant prior to harvest and the major cause of amylase activity in temperate climates (Nielsen 1984; Mares 1993; Lunn et al. 2002). The risk of pre-harvest sprouting also depends on the variety. For instance, varieties with awns increase ear wettability during precipitation events, i.e.

[3] 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 3.8%.
[4] This threshold can be different in other wheat markets. For instance, the United Kingdom has a more stringent threshold of 250 seconds (Lunn et al. 2002) and high-quality wheat has a threshold of 300 seconds in Australia (Biddulph et al. 2008).

increase the risk of amylase activity in grains, and varieties with waxes on ears increase water repellency, i.e. decrease the risk of amylase activity in grains (King and Wettstein-Knowles 2000). Secondly, precipitation can delay harvests of ripe wheat by increasing soil moisture contents that prevent the use of combines due to the risk of soil compaction and a delayed harvest tends to increase amylase activity, i.e. amplify the risk of a downgrading (Olaerts et al. 2016).

Temperature effects on the activation of amylase proteins, however, are ambiguous. Research has found potentially beneficial, harmful or nonexistent temperature effects on amylase activity or similar measures such as pre-harvest sprouting tolerance (e.g. Nielsen 1984; Smith and Gooding 1999; Lunn et al. 2002; Biddulph et al. 2007; Mares and Mrva 2008; Barnard and Smith 2009; Barnard and Smith 2012).

In summary, bread and biscuit wheat with critical amylase activity in grains has poor baking quality. This low-quality wheat can only be used as animal feed sold at a much lower price. Research finds precipitation to be one of the most important determinants of amylase activity. Thus, we here focus on precipitation effects, which we assume to increase the risk of a downgrading, and control for temperature, varietal and other environmental effects.

3. Methods

We build on section 2. Background to develop a novel model that estimates precipitation effects on the risk of a downgrading of bread and biscuit wheat to feed wheat and to simulate profit reductions after a downgrading to feed wheat.[5] The estimation of precipitation effects on the risk of a downgrading and the simulation of profit reductions after a downgrading are independent of each other.

3.1 Estimation of precipitation effects

We use the linear probability model with variety and location fixed effects shown in equation (2) to estimate overall precipitation effects on the probability of a downgrading of bread and biscuit wheat to animal feed wheat due to poor baking quality. The variety fixed effects α_v absorb unobserved variety-specific confounders (e.g. genetics) and the location fixed effects γ_i absorb unobserved, time-invariant confounders (e.g. soil properties) that may be correlated with precipitation.

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

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 (i.e. the industry

[5] All code is publicly provided on github: (insert link after peer-review)

measure for amylase activity) below 220 seconds (1 = downgrading; 0 = no downgrading). 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 correlation with cumulative precipitation CP_{it} and the error term ε_{ivt} summarizes remaining effects. The parameters β and ∂ are estimated using the least squares estimator. We are particularly interested in β, which shows the marginal effect of cumulative precipitation CP_{it} on the risk of a downgrading.

The literature shows that especially weather towards the end of the growing season affects amylase activity (Mares 1993; Barnard and Smith 2012; Olaerts et al. 2016). Therefore, we use two measurement periods for the control weather variables and divide these two periods by a certain number of days prior to harvest n. In accordance with the measurement period of cumulative precipitation CP_{it}, the first period lasts from harvest to n days prior to harvest. The second period lasts from planting to the beginning of the first period. We use optimal degree-days and heat degree-days in both periods to measure nonlinear temperature effects on the risk of a downgrading. Optimal degree-days measure temperature loads[6] between 5°C and an upper heat threshold h and heat degree-days measure temperature loads above the heat threshold h (see e.g. D'Agostino and Schlenker, 2016). In addition, we control for cumulative precipitation in the second period (precipitation in the first period is our variable of interest). The literature does not indicate a suitable number of days prior to harvest n used to divide the measurement periods and a suitable heat thresholds h used to differentiate between optimal- and heat degree-days in the context of amylase activity. Thus, we run a grid search and estimate equation (2) for each combination of number of days prior to harvest n and heat threshold h. Subsequently, we pick the combination with largest goodness of fit, i.e. the model with lowest residual sum of squares[7].

Identification strategy

We aim to identify precipitation effects on the risk of a downgrading of bread and biscuit wheat to feed wheat due to poor baking quality. There are several reasons why the model described above is suitable to identify these precipitation effects. 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, the model implicitly accounts for short-term adaptation as a response to weather risk exposure, for instance by harvesting wheat just before full ripeness. Thirdly, we minimize omitted variable bias by controlling for a myriad of potential confounders and building our model based on agronomic literature. More specifically, we control for observed temperature effects in

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

[7] We use different specifications as robustness checks. These robustness checks confirm our key findings.

period 1 (close to harvest) and period 2 (from planting to the beginning of period 1) that may be correlated with precipitation effects CP_{it} in period 1. We also control for precipitation effects in period 2 that may be correlated with precipitation effects CP_{it} in period 1. In addition, we control for many unobserved confounders by using variety and location fixed effects. Thirdly, the use of field trial data supports the identification of precipitation effects on the risk of a downgrading because field management is standardized, i.e. any type of production risk exposure and potential changes in input or output prices do not change field management. Fourthly, a linear probability model avoids the incidental parameter problem that may cause biased estimates in the presence of fixed effects in generalized linear models such as logit or probit regression (Lancaster, 2000). Yet, we confirm the results from the linear probability model with generalized linear models in a robustness check.

Error terms in linear probability models are heteroscedastic and we also expect them to be spatially autocorrelated. Thus, we cluster standard errors by variety.

We address the challenge of measurement errors in the weather variables that might bias our estimates (Auffhammer et al. 2013) by using homogenized and quality-checked weather data provided by experts in climatology and meteorology. Measurement errors in the binary dependent variable, if there are any, are unlikely to correlate with weather exposure and thus unlikely to bias our estimates (Hausman et al. 2001).

3.2 Simulation of profit reductions

We simulate profit reductions after a downgrading to feed wheat by following equation (3). The profit reduction after a downgrading of variety v harvested at location i and 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 Δp_{vt}. The yield quantity of variety v harvested at location i in year t is denoted as y_{vit}.

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

We assume production costs to be independent of a downgrading event because the Hagberg Falling Number (i.e. the measure to determine a downgrading) is measured after harvest at grain elevators and amylase activity emerges after all inputs have been applied on the field.

4. Data

We combine agronomic data with weather data to estimate precipitation effects on the risk of a downgrading to feed wheat and we combine agronomic data with price data to simulate profit reductions after downgrading events.

4.1 Agronomic data

We use a panel dataset from the Swiss wheat varieties trial network provided by Agroscope (the Swiss Confederation's centre of excellence for agricultural research) and swiss granum (Swiss industry organization for cereals, oilseeds and protein crops) that consists of 1'859 bread and biscuit winter wheat observations of commercially available varieties measured 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 ten representative locations shown in figure 2. Locations reflect the heterogeneity in agri-environmental conditions in Swiss wheat production. A large share of winter wheat production takes place in the plain regions close to the field trial locations.

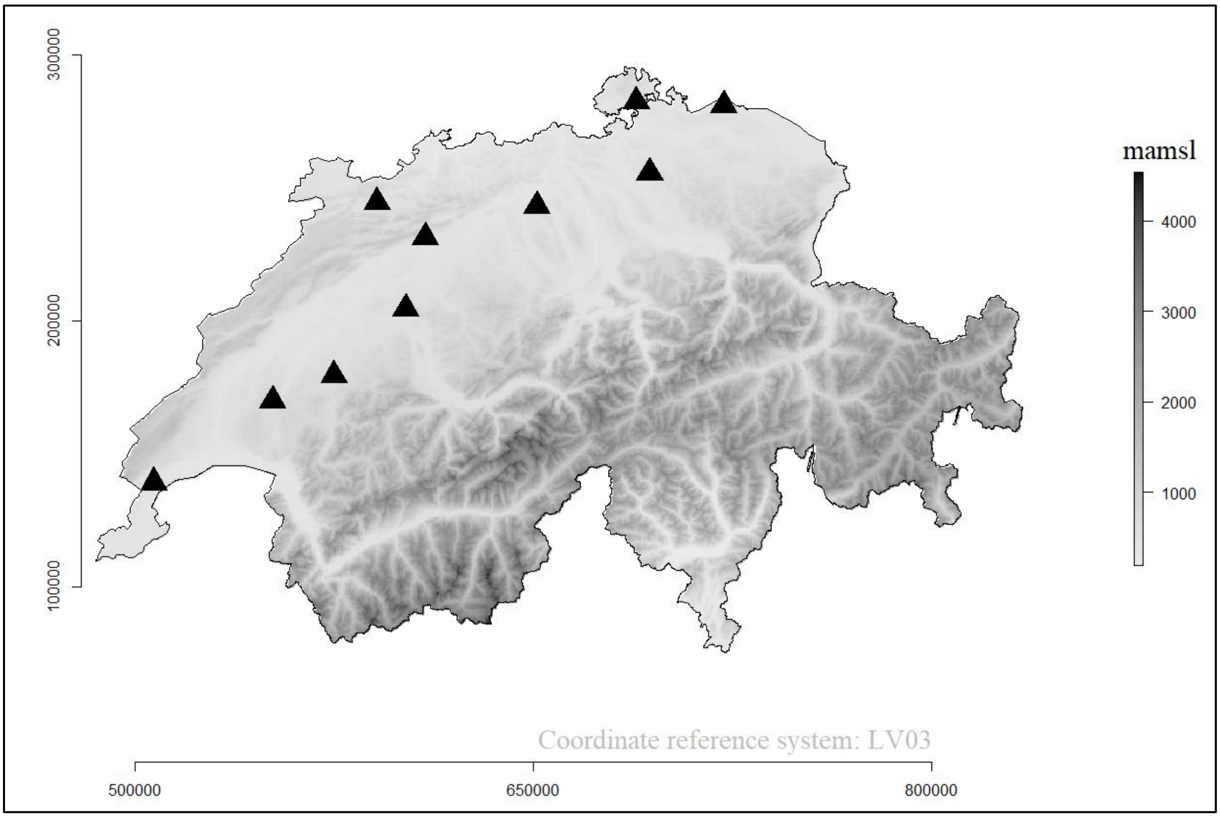


Figure 2: Locations of varietal field trials

Note: *mamsl* is meters above mean sea level.

The portfolio of varieties is the same at each location within the same year so that the dataset reflects spatial variability. We only consider varieties that are several years in the panel and that are offered to Swiss farmers so that the dataset also reflects temporal variability and represents commercially grown bread and biscuit wheat varieties. We follow Swiss market conditions and downgrade bread and biscuit wheat observations with a Hagberg Falling Number below 220 seconds to feed wheat. Table 1 provides sample statistics including the number of downgrading events and figure AX in the appendix shows historical distributions of Hagberg Falling Numbers in seconds and crop yield quantities in deci-tons per hectare [dt / ha].

Table 1. Overview of downgrading events in our sample, 2008-2019

Price class	Bread wheat			Biscuit wheat	Total
	Top	I	II		
Observations	697	652	377	105	1859
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 seconds is downgraded to feed wheat.

Management in the varieties trial network is standardized. Planting takes place under suitable weather conditions around mid-October and harvest is, depending on weather conditions and speed of crop growth, between July and early August of the consecutive year (see Figure X in the online appendix for the distribution of planting and harvest dates). There is no response in management decisions to changes in input our output prices and no adjustments of on-field inputs during the growing season. Wheat can be harvested just before full ripeness and post-dried to prevent weather risk exposure that may affect amylase activity. Herrera et al. (2018) provide more details regarding the standardized input-use.

4.2 Weather data

We derive location-specific daily precipitation amounts, daily minimum temperature and daily maximum temperature from homogenized and quality-checked gridded datasets (spatial resolution of 1 x 1 km) provided by the Federal Office of Meteorology and Climatology (Frei, 2014))[8]. 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 micro-climates. 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).

We use daily minimum and maximum temperatures to calculate the control variables optimal degree-days and heat degree-days (see section 3.1 Estimation of precipitation effects). More specifically, we follow previous research (e.g. Tack et al. 2015; Gammans et al. 2017; Ortiz-Bobea et al. 2018; Bucheli

[8] More detailed documentation can be found here: https://hyd.ifu.ethz.ch/research-data-models/meteoswiss.html (last accessed February 08, 2022).

et al. 2022) and estimate daily temperature curves[9] to consider intra-day 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.

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. These producer reference prices are a good indicator of realized producer prices (see section 2.2 The Swiss wheat market). As shown in figure AX in the appendix, producer reference prices did not change between 2014 to 2019 (last year in our panel) and show very little volatility prior to 2014. All prices are in Swiss francs per deci-ton (Swiss francs / 100 kg).

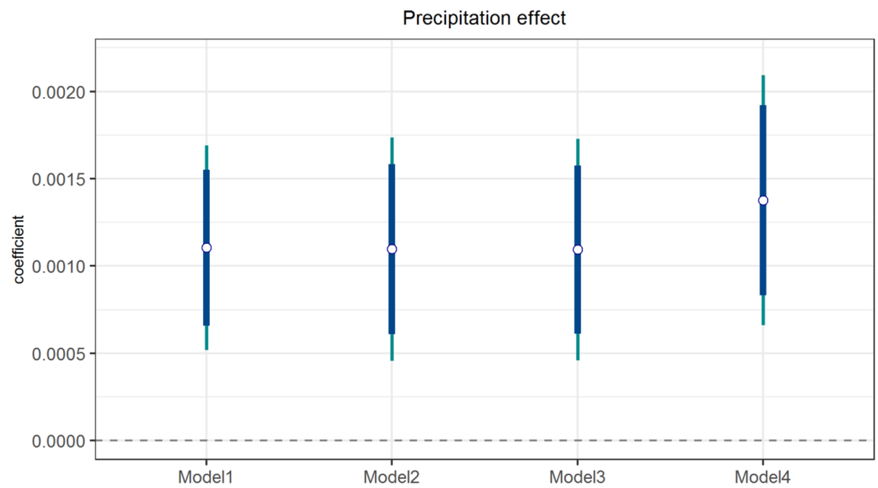
5. Results

We first present estimated precipitation effects on the probability of a downgrading and then put forward the simulation of economic losses after a downgrading.

5.1 Precipitation effects on the risk of a downgrading

Precipitation up to a month prior to harvest increases the risk of a downgrading significantly. This is shown in figure 3, which shows estimated precipitation effects of different model specifications of equation (2) in a coefficient plot. More specifically, we estimate that each additional millimeter of precipitation increases the risk of a downgrading by 0.1%. This point estimate is robust to different model specifications (Model 1-4 in figure 3). The grid search indicates period 1 to last from harvest to 31 days prior to harvest and a heat threshold of 27°C for the differentiation of optimal degree-days and heat degree-days.

[9] 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.



Period 1 (before harvest)	Optimal degree-days	▪			▪
	Heat degree-days	▪			▪
Period 2 (sowing to period1)	Precipitation	▪	▪		▪
	Optimal degree-days	▪			
	Heat degree-days	▪			
Fixed effects	Variety	yes	yes	yes	yes
	Location	yes	yes	yes	yes
Estimated parameter	Days prior to harvest	31	31	31	31
	Heat threshold [°C]	27	--	--	27
Goodness of fit	Adj. R-squared [%]	15.03	11.63	11.30	14.23
	AIC	-753	-684	-678	-738

Figure 3. Estimated precipitation effects for different models

Note: Standard errors are clustered by variety. Estimated parameters derived from a grid search.

5.2 Downgrading effects on economic performance

A downgrading causes large profit reductions of up to 1’445 Swiss francs per hectare. Downgrading events occur rarely and not on a regular basis. The risk of a downgrading can be of idiosyncratic or systemic nature and affects varieties in all price classes (i.e. *Top*, *I*, *II*, *Biscuit*).

Figure 4 (subpanel a) illustrates simulated profit reductions after a downgrading. All price classes can be affected by a downgrading and losses are largest for varieties in the *Top* price class. Figure 4 (subpanel b) shows the historical frequency of downgrading events. Downgrading events occur rarely and, in some years, there is not a single downgraded observations. The risk of a downgrading can be idiosyncratic (e.g. in 2017) or of systemic nature (e.g. 2014).

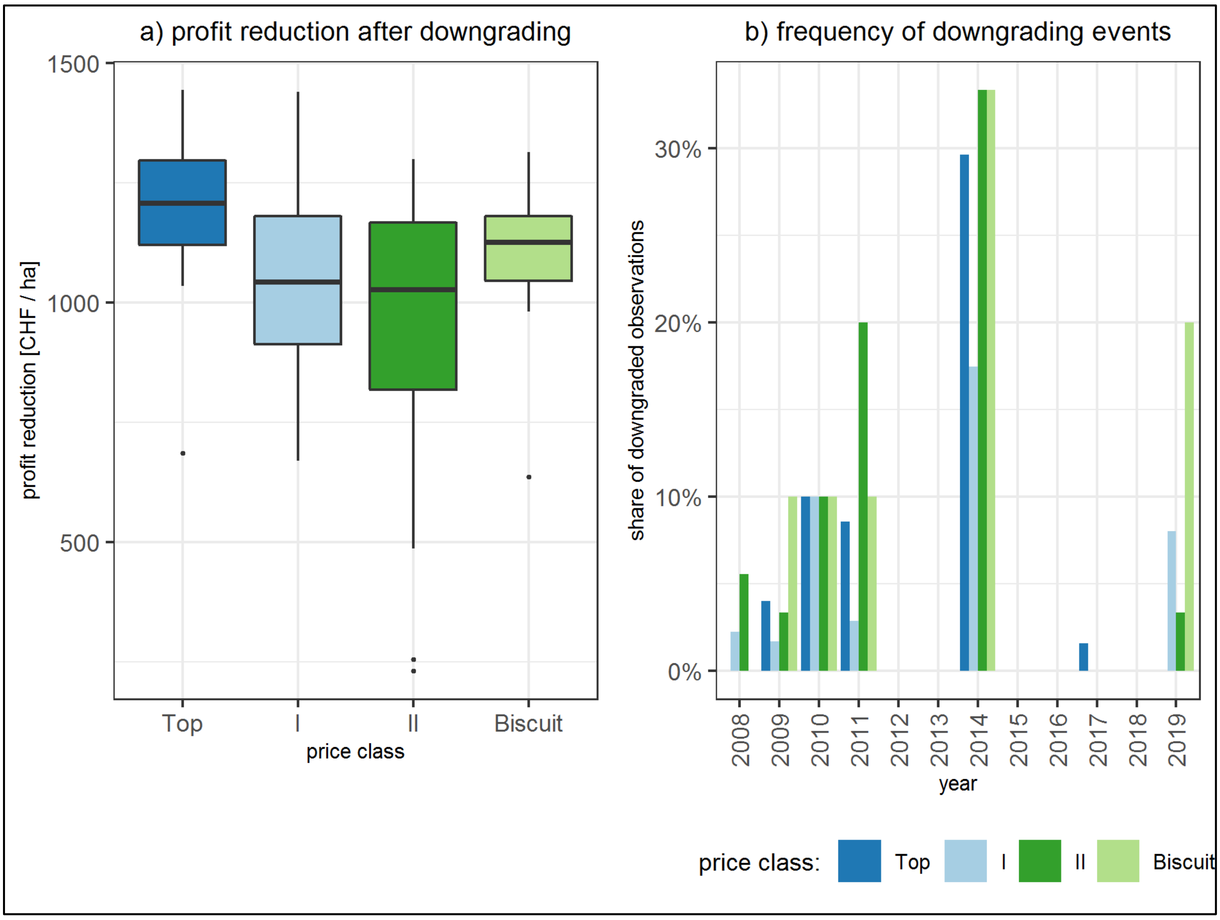


Figure 4. Profit reduction after a downgrading and frequency of downgrading events

Table 2 shows the expected profit reductions, which considers both the frequency and economic magnitude of a downgrading. The expected profit reduction ranges between 44.37 CHF/ha for varieties belonging to the price class *I* and 86.13 CHF / ha for varieties belonging to the price class *Biscuit*.

Table 2. Expected profit reductions due to a downgrading.

Price class	Top (n=668)	I (n=618)	II (n=365)	Biscuit (n=100)
Expected profit reduction [CHF / ha]	54.02	44.37	56.41	86.13

Note: CHF is Swiss francs and *ha* hectare.

6. Discussion and conclusion

This article estimates precipitation effects on the risk of a downgrading of bread and biscuit wheat to animal feed wheat and simulates profit reductions that result from downgrading events. Thereby, this article highlights the economic relevance of weather-dependent yield quality, informs various actors within food systems about the underlying risk exposure and provides a basis for improved risk management and breeding programs. We find that precipitation a month prior to harvest increases the risk of a downgrading and that a downgrading of bread and biscuit wheat to animal feed wheat causes large economic losses for wheat producers. Downgrading events occur rarely and not on a regular basis. The risk of a downgrading to animal feed wheat can be of idiosyncratic or systemic nature. These findings have implications for several actors in food systems.

Farmers have limited capacities to respond to weather conditions that increase the risk of a downgrading because risk exposure occurs after all inputs have been applied towards the end of the season. Thus, the choice of variety is important to reduce the risk of a downgrading on the field. In addition, equipment to harvest as soon as possible (i.e. not delay the harvest) and to post-dry wheat after an early harvest can also decrease the risk of a downgrading on the farm. Insurance solutions could complement these on-farm strategies. The risk of a downgrading shows high insurability because downgrading events are rare but of large economic consequences. Weather index insurance solutions might be particularly viable because this type of insurance avoids moral hazard problems (e.g. delaying a harvest to increase the probability of a payout).

The risk of a downgrading also affects input suppliers and extension services that provide sales advice to farmers. Downstream actors should also consider the risk of a downgrading because it affects their supply chain management, especially in years with systemic downgrading events. Blending the harvest of different farmers is risky because even small amounts of amylase proteins can cause a loss of baking quality. Thus, food systems would benefit from a stronger focus on the oppression of amylase proteins in breeding programs.

Policymakers should be aware of the economic relevance of crop yield quality and reflect this aspect in agricultural policies. Moreover, policymakers can support the provision of effective risk-reducing tools by supporting and evaluating breeding efforts and by providing a legal framework that facilitates the implementation of other tools such as insurances.

Future research should consider crop quality in economic risk assessments. It should also consider other quality risks (e.g. protein content), other production systems and different crops for which quality is price-relevant. Moreover, future research can support the development and implementation of risk management tools.

7. References

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