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Very little worth knowing is taught by fear.

Robin Hobb, Assassin's Apprentice

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Introduction

Climate change represents one of the most pressing and complex challenges, reshaping economies, ecosystems, and human behavior. Its far-reaching consequences extend across various sectors, with agriculture being particularly vulnerable to the associated impacts. Rising temperatures coupled with increasing frequency and intensity of extreme events pose severe threats to agricultural productivity, leading to economic instability and threatening food security (IPCC 2022). These disruptions further shape adaptation capabilities and international policy. To effectively address climate change, a comprehensive understanding of its various dimensions is required.

First, it is essential to understand the physical impact of climate change on natural systems. Agriculture is one of the sectors most vulnerable to climate variability, as agricultural land is directly exposed to changing weather. While significant progress has been made in assessing these impacts, considerable uncertainty remains regarding the estimates of climate change on agricultural yields. This uncertainty presents significant challenges for policymakers and farmers alike as they attempt to devise appropriate strategies for mitigation and adaptation in the face of evolving climate conditions. Second, interdependencies between climate and economic agents are becoming increasingly complex. The relationship between climate and human behavior is circular in nature: Climate impacts, such as frost, heavy rainfall, and temperature variability, are critical factors, and agricultural productivity is directly impacted by it. Farmers are increasingly facing challenges, such as shifting growing seasons, spring frost, drought impacts, and heavy precipitation, all of which threaten both individual livelihoods and the global food supply. These climate impacts, however, not only shape the environment that we must adapt to but also influence human behavior. Climate perceptions and climate beliefs define our scope of action. Where past behavior has shaped the conditions we must now adapt to. Moreover, climate change is a global issue that demands international cooperation to mitigate its effects. Despite the success of the Paris Agreement, we observe little progress in climate change mitigation in almost all countries. Current emissions levels exceed those pledged by nations, and even full compliance with existing commitments is unlikely to prevent a global temperature increase of more than 2°C, the threshold widely regarded as critical for avoiding the most catastrophic consequences of climate change.

This thesis comprises three chapters, each addressing one of the different obstacles outlined before. The first project focuses on assessing climate impacts on agricultural yield, with the goal of further understanding the physical impacts of climate change. The second chapter examines the adaptive behavior of farmers, investigating through survey data how they respond to perceived climate risks and the extent to which they are willing to adopt adaptive measures. The third chapter explores the strategic behavior of agents in the context of international cooperation, using a principal-agent framework experiment to test theoretical predictions. Together, these chapters explore key themes related to uncertainty, the interaction between natural and human systems, and decision-making under constraints.

More precisely, in the first chapter of my thesis, I analyze climate impacts on agricultural yields, with a particular focus on perennial crops. Perennial crops present unique challenges for climate modeling due to their sensitivity to weather conditions throughout the year and their long-term cultivation cycles (Lobell and Field 2011). Perennial crops are both of very high nutritional and economic value (Leisner 2020; Siegle et al. 2024). Despite the importance of perennial crops to global food production, studies examining the climate impacts on these crops are relatively scarce (Gunathilaka et al. 2018). To address this gap, I use a unique longitudinal orchard-level dataset from Switzerland to investigate the effects of climate change on apple yields. In doing so, I pay particular attention to the impact of frost during different phenological development stages. I model different phenological stages based on temperature, introducing a dynamic component into the impact assessment. The model very accurately predicts past yield. Furthermore, I use the estimated relationship to then project future yield risk till the end of the century. The results show that spring frost, increasing heat days, and changes to winter chilling have a significant negative impact on apple productivity. I find a shift in the growing season, where temperature changes will cause earlier blooming dates, particularly pronounced under higher-emission scenarios. Additionally, I find future yield gains under various climate models and emission scenarios. However, climate and model uncertainty limit the extent of anthropogenic climate change for which reliable predictions are possible.

Building on the insights from the first chapter, the second chapter shifts focus to the adaptive behavior of farmers in response to climate risks. The perennial crop sector faces unique challenges due to its path dependencies as plants are grown for up to 30 years. In light of this, understanding the adaptation behavior of perennial crop farmers and having this long-term perspective are crucial for effective adaptation. Adaptation, however, does not occur in a vacuum. Effective adaptation requires a willingness to change behavior, which in turn is dependent on climate change belief, climate change perception, economic consideration, and the perceived costs and benefits of potential adaptation measures (Chatrchyan et al. 2017; Niles and Mueller 2016; Fishbein and Ajzen 2011). I investigate the role of farmers' adaptation behavior by eliciting factors such as climate impact, perceptions, and beliefs through an online survey directed at fruit farmers in Switzerland. I find larger past climate impacts due to frost compared to drought. This, however, does not translate to farmers' concerns, as they are more concerned about future drought impact compared to frost. Results show that farmers are more skilled at identifying temperature trends than frost and precipitation patterns, with the accuracy of precipitation perception varying based on the irrigation systems in use. In addition to farmers' main concerns being of a regulatory nature, the majority of them exhibit concerns about climate change. Farmers exhibiting climate skepticism display lower policy support for climate mitigation compared to those who believe in anthropogenic climate change. Interestingly, skeptics display a higher willingness to adapt, highlighting the complex nature of adaptation behavior in the agricultural sector.

The third chapter moves beyond the agricultural focus to consider the broader question of international cooperation in mitigating climate change. Symbolically, I transition from single-author papers to my first co-authored chapter, which includes a collaboration with the University of Bologna, also furthering international cooperation. Climate policies are often governed by a principal-agent dynamic, where one party (the agent) acts on behalf of another (the principal), particularly in the context of domestic and international policy interactions. Theoretical models through the lens of economic policy and game theory predict that under specific circumstances, it is optimal for the principal to delegate strategically, meaning to delegate to an agent who exhibits different preferences with regard to public goods than they do themselves. This stands in contrast with the experimental literature, hinting at the concept of conditional cooperation. We test these theoretical predictions through laboratory and online experiments. We find that principals delegate to agents with a higher evaluation of the public good if they expect that the other principal does the same, contrasting theoretical predictions that follow when players only care about their own payoffs: in this scenario, delegating to agents with a higher evaluation of benefits is never in the best interest of the principals. Our results suggest that the race to the bottom caused by strategic delegation in public goods contexts may be considerably less severe than what is discussed in the theoretical economic literature.

The overarching goal of this thesis is to enhance our understanding of the mechanisms driving climate change impacts, both in terms of natural systems and human behavior. By employing diverse analytical methods, this research seeks to inform the development of more effective adaptation strategies and international policy frameworks. Understanding the interplay between nature and human systems, as well as the decision-making processes of various actors, will prove necessary in order to provide instructive policy guidance for the design of effective adaptation policies as well as international policy frameworks.

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Chapter 1

Yield Risks for Perennial Crops under Changing Climate Conditions

Abstract

Agriculture is among the sectors most vulnerable to climate change, with perennial crops like apple orchards particularly at risk due to their long growth cycles and limited adaptive capacity. This study examines future yield risks using a unique orchard-level dataset and the Phenoflex model to predict phenological stages. We develop phenology-specific frost indicators and evaluate temperature effects while calibrating different chilling models. Our findings indicate a trend toward earlier flowering stages, higher average temperatures, fewer total spring frost days but more frost days dependent on specific phenological phases, and an increase in extreme heat events. Frost and extreme heat events show significant negative impacts on productivity, with frost effects during full bloom having the greatest effect. Overall, we find yield increases rather than losses over time, driven by warmer temperatures and reduced frost damage. However, uncertainties in climate projections and model assumptions limit the precision of these yield predictions, especially over long timescales. Under future climate scenarios, yield gains vary based on emissions pathways: the high-emission RCP8.5 scenario shows the largest yield increases, likely due to fewer frost days and a warmer growing season, while the lower-emission RCP2.6 scenario is associated with smaller yield gains.

Keywords: climate impact, yield risk, panel analysis, agriculture, phenology, spring frost

JEL-codes: Q15, Q54

1.1 Introduction

Weather effects such as frost, heavy rainfall, and temperature variability are critical factors and can have a negative impact on agricultural productivity, consequently affecting farmers' livelihoods. The agriculture sector is one of the most vulnerable to the effects of climate change. While studies on the impact of climate on major annual crops such as wheat, soybeans, rice, and maize are prominent (Schlenker and Roberts (2009); Welch et al. (2010); Deschênes and Greenstone (2007); Schlenker and Lobell (2010); Asseng et al. (2015)), there are few comprehensive assessments of the impact of climate on perennial crops. Perennial crops are of high nutritional and economic value. While crops like wheat, soybeans, rice, and maize provide essential calories, most fruits are rich in micro-nutrients, playing a vital role in addressing the challenges of maintaining a healthy diet in today's agri-food landscape (Leisner 2020). Economically, perennials are high-value crops, and their international trade has surged in recent years, making them an important source of income for developing countries (Siegle et al. 2024). In addition, perennial crops are especially susceptible to climate change, as individual plants are grown for up to 30 years, limiting adaptability in the short term. Unlike annual crops, perennial crops are affected by weather at any time of the year, not just during the growing season and climate effects can transfer to the following years. Furthermore, fruit trees are very susceptible to the effects of frost. The future effects of changes in flowering times in the growing season in relation to climate change have not yet been sufficiently investigated.

In this paper, we assess the potential yield risks for fruit trees due to climate change. Beyond commonly considered variables, we examine yield risk due to spring frost by quantifying phenology-specific frost events. Additionally, we account for factors outside the traditional growing season, such as winter chilling requirements. By modeling the historical relationships, we use the most accurate predictive model to project future yields and assess changes under different emission scenarios and climate models.

The lack of studies investigating the effects of climate change on perennial crops poses a particular challenge for statistical modeling of these effects. This paper advances the existing literature on climate impacts on agricultural yields by focusing specifically on perennial crops, addressing a critical research gap in modeling climate effects – particularly spring frost risk. Unlike previous studies, we incorporate frost indicators based on a phenology model, providing a more detailed understanding of the relationship between crop developmental stages and frost exposure. To address this, we use a unique orchard-level panel dataset on apple production in Switzerland covering over 440 orchards for the years 1997 to 2019. To model the impact of spring frost, we predict the flowering stage using the Phenoflex model and incorporate non-linear temperature effects with growing degree days and growing degree hours. We capture the influence of winter chilling and control for all time-invariant unobserved heterogeneity. Additionally, we control for perennial-specific dynamics such as biennial bearing, which has been neglected in the literature so far. Subsequently, we build different models based on both biophysical processes and variable selection using random forests and evaluate their predictive power through various out-of-sample validations, selecting the best-performing model. The estimated yield-climate relationship is then used with climate change scenarios from the EURO-CORDEX ensemble to assess potential impacts through 2099. As the choice of climate model can strongly influence the yield projection, we project future yield development based on nine different climate models. We model percentage changes in yields for three different time horizons and for three possible emission scenarios.

We observe a general increase in average temperatures and a rise in the frequency of extremely hot days, accompanied by an overall reduction in frost days. However, phenology-dependent frost days are, on average, more frequent than in the reference period, though they decline across future time horizons and emissions scenarios (RCPs), with a particularly notable reduction under RCP8.5. Precipitation patterns show no clear trend. Predicted changes in the bloom stage indicate that flowering is likely to occur earlier on average, particularly under high-emission scenarios. We observe a positive effect of increased temperatures on yields, the effect, however, being bound by an upper limit. Heat stress has a significant negative impact on agricultural productivity, as trees shift into "survival mode" slowing down production. We also observe large, significant negative impacts from phenology-specific frost events, with the most severe impacts occurring during full bloom. Our projections based on the climate-yield relationship suggest an overall increase in future yields, with the degree of gain varying across different climate and emission scenarios but showing a consistently positive trend. Notably, yield gains are more pronounced under high-emission scenarios, likely due to a reduction in frost risks and a warmer growing season that outweighs the negative effects of increased heat stress and shifts in blooming dates.

This paper proceeds as follows: In Section 2.2, we review the relevant literature. Section 1.3 describes the data sources we use for the analysis, including temperature, precipitation, agricultural, and phenological data. In Section 1.4, we outline our methodology, covering data preparation, PhenoFlex model specifications, winter chill models, and climate variable derivation. We also detail our statistical modeling approach, variable selection, and out-of-sample predictions. In Section 1.5, we present the climate scenario data and yield projections. Finally, we conclude with a discussion of our key findings in Section 2.5.

1.2 Related Literature

Given the numerous challenges associated with assessing climate impacts on agriculture using only cross-sectional data, a variety of different approaches are being discussed. According to Maharjan and Joshi (2013), there are at least four different methodologies to assess the impact of climate change on agriculture: crop simulations from agronomic research, the hedonic approach, time series, and panel models. Since the early 2000s, a large literature on panel data has emerged (Kolstad and Moore 2020). They use panel methods and high-frequency (e.g., year-to-year) variations in temperature, precipitation, and other climatic variables to determine the economic impact of these variables. Blanc and Schlenker (2020) provide an overview of the usage of panel data for the assessment of the impact of climate change on agricultural products. Dell et al. (2014) state, that by harnessing exogenous variation over time within a given spatial unit, these studies help to credibly identify the breadth of channels linking weather and the economy, heterogeneous treatment effects across different types of locations, and nonlinear effects of weather variables.[1]

Panel models can be used not only to evaluate the impacts of past climate but also to project future yield. Research by Asseng et al. (2015) shows that statistical models performed equally well or even better than elaborate agronomic models in predicting yield. One key advantage is that panel models can assess prediction performance using out-of-sample validation. As mentioned before, panel data allows for the use of fixed effects (Blanc and Schlenker 2020). This is commonly done when assessing the impact of climate on agriculture (e.g., Deschênes and Greenstone (2007); Schlenker et al. (2006); Schlenker and Roberts (2008); Schlenker and Roberts (2009); Seo (2013); Fisher et al. (2012); D'Agostino and Schlenker (2016)). Most of the studied panel units are country, state or district level. An exception is the work by Welch et al. (2010), which uses farm-level data to examine opposing sensitivities of rice yield to minimum and maximum temperatures. They highlight the importance of having such fine-scaled data to analyze the complex relationship between weather, climate, and agricultural yield.

While studies of the effects of climate on major annual crops such as wheat, soybeans, rice, and maize have been prominent, comprehensive assessments of the effects of climate on perennial crops are rare, especially when focused on panel data analysis. Lobell and Field (2011) state that modeling climate impact on perennial crops presents unique challenges, due to the slow growth complicating experimental warming trials. Furthermore, there are far fewer models to describe perennial growth. In addition, perennial crops are affected by climate throughout the year and not just during the growing season. There are additional variables, such as winter chilling, which should be taken into account as perennial crops have to satisfy a certain chilling requirement to kick off bud break. These chilling requirements are cultivar-specific. Atkinson et al. (2013) suggest that winter chilling has declined and is predicted to continue to do so, which is a potential factor for yield risk.

[1] They summarize various studies, out of which we included the ones focusing on crop yields or agricultural output in Table 5 in the Appendix.

There are some studies on perennial crops: Gunathilaka et al. (2017) use monthly panel data from 40 different tea estates in Sri Lanka over a 15-year period to assess weather impacts on production. Their predictions show a negative proportional impact from increased rainfall and increased average temperature and up to a 12% decline in annual tea production for the highest emission scenario. Lobell and Field (2011) analyze perennial crops in a changing climate in California. After analyzing 20 of the most valuable perennial crops using a combination of statistical crop models and down-scaled climate model projections, they find clear weather responses for only four models, with another four yielding significant but less robust relationships. However, perennial crops such as apples and pears are not included in this analysis. Deschenes and Kolstad (2011) also focus on climate impacts in the State of California. They assess the impacts on agricultural profits. Their preferred estimates show a negative impact on profits by the end of the century. Hong et al. (2020) analyze the impact of climate change and ozone on perennial crops. They focus on almonds, grapes, and nectarines. They find significant negative responses to ambient ozone, where ozone reduction could even overpower the effects of warming, leading to a net gain in yield for some crops. However, future warming could then potentially lead to yield losses in the future. They do not include apples or phenological variables. Parker et al. (2020) discuss potential impacts and stress induced by more frequent, intense, and longer duration heat extremes on perennial crops. They state that perennial crop sensitivity can vary widely across crops.

In Switzerland, Dalhaus et al. (2020) analyze the effect of extreme weather on apple quality. They use regression analysis to estimate the impact of temperature changes during apple flowering on apple price and yield. They find that spring frost events lead to a dip in farm gate price and thus revenue reductions of up to 2% per hour of exposure. There is, however, still much uncertainty when it comes to the future risk of spring frost on apple production. We build upon their work by incorporating dynamic predictions of bloom dates and frost measurements. Additionally, unlike Dalhaus et al. (2020), which focuses solely on the quantification of past impacts, our approach extends to forecasting potential future developments. The shift in blooming dates to earlier dates could result in an increased spring frost risk (Lhotka and Brönnimann 2020). Eccel et al. (2009) find that spring frost risk has already declined at present and is likely to be constant or slightly lower in the future. Unterberger et al. (2018) also analyze how climate change affects the spring frost risk for apple farmers. Combining a phenological model with climate projections in Austria, they predict a mean advance of blooming of 1.6 ± 0.9 days per decade. They further note that the overall frost risk for apples will remain, even in warmer climates. Hence, there is still uncertainty about the degree of future spring frost risk. With continuing uncertainty about spring frost risk, the uncertainty of yield risk for apple farmers remains.

In conclusion, this paper builds on and complements the existing literature on climate impact evaluation on agricultural yields. Firstly, it addresses a research gap in the analysis of climate impacts on perennial crops, which are arguably more susceptible to future climate changes due to path dependencies and short-term adaptation challenges. We include perennial-specific factors, such as lagged frost and winter chilling. Second, this study is based on a unique orchard-level dataset, allowing a much finer-scaled analysis. Additionally, contrasting prior research, this project introduces phenology-dependent frost indicators based on a phenology model.

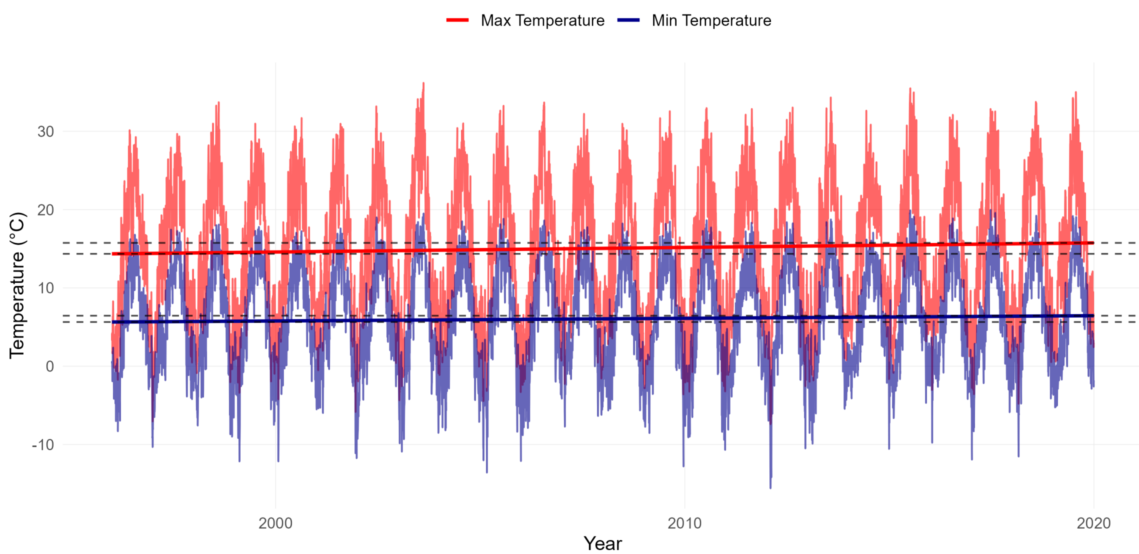
1.3 Data

We integrate multiple data sources, including temperature records, agricultural data, and climate scenario projections to conduct our analysis.

1.3.1 Temperature and Precipitation Records

We use daily temperature measurements from ground stations provided by MeteoSwiss, the Swiss Federal Office of Meteorology and Climatology. Limitations in ground station data typically arise when networks are sparse, or records are inconsistent, challenges that are often more pronounced in low- and middle-income countries. However, Switzerland exhibits a dense network of ground stations that offer highly accurate, location-specific climate data, making them a reliable source. After cleaning and selecting suitable stations, based on data availability and elevation, we have a dataset consisting of 37 temperature measurement sites as well as 82 precipitation measurement sites. We restricted the data to years 1997–2019 to match the farm-level yield data. Daily minimum and maximum temperature over the years 1997–2019 averaged across all stations has approximately increased by 1°C.

Figure 1: Temperature Over Time



Notes: Daily minimum (blue) and maximum (red) temperature averaged across all stations from 01/01/1997–31/12/2019.

1.3.2 Orchard-Level Data

We rely on orchard-level panel data on apple production provided by the Swiss Federal research station Agroscope. As the data contains sensitive economic data, access is restricted and needs to be granted by the Swiss Confederation's Center of Excellence for Agricultural Research Agroscope. To our knowledge, there is no comparable dataset giving the same fine-scaled (orchard-level) assessment of apple production. The dataset contains more than 4,098 observations on 53 different apple varieties for over 440 orchards in 12 cantons. The yearly observed variables include yields (kg/ha), yield per effort (kg/h), revenue (CHF/kg and CHF/ha), farm-gate prices (CHF/kg), area (ha), a binary indicator for organic, and age of the particular trees (year after planting). Each farm has its own Swiss area code. This dataset was matched with an area code dataset[2], matching each area code with its respective village or city and canton information. Due to an implausibly high revenue per ha, we dropped one of the 4,098 observations. The most common apple varieties are Golden Delicious (14.4%), Gala (14.3%), and Braeburn (8.6%).[3] The cantons with, on average, the highest revenue (CHF/ha) are the cantons Vaud (13.1%), Geneva (11.9%), and Valais (9.91%).

[2]The area code dataset contains all names, perimeters, and postcodes of all localities in Switzerland and the Principality of Liechtenstein and is provided by the Federal Office of Topography Swisstopo.

[3]We combined all different Gala varieties into one common variety called "Gala".

Table 1: Descriptive Statistics of Orchard Data

Variable	**Mean**	**Min**	**Max**	**Sd**
Revenue (CHF/ha)	27,981.24	469.56	156,493.17	17,680.33
Farm gate price (CHF/kg)	0.98	0.02	15.99	0.71
Yield/effort (kg/h)	130.76	3.05	15,224.91	339.04
Yield (kg/ha)	32,584.92	220.51	173,143.54	18,008.82

Notes: Summary statistics of orchard-level data, including revenue (in Swiss Francs per hectare and per kilogram, yield per labor effort (kilograms per hour), and yield (kilograms per hectare)

For each orchard, we restricted the dataset to the apple variety with the longest time series.[4] The most prevalent varieties are still Gala, Golden Delicious, and Braeburn. Furthermore, we removed duplicate entries to enhance data accuracy and consistency. Throughout our time series 1997–2019, there are clear annual fluctuations in yield. Part of this is attributable to "biennial bearing", that is, the fluctuation of fruit yield in a biennial rhythm, often triggered by weather influences. In apples, this leads to the so-called "apple years", which alternate directly with years of very low yield. If the tree has many or too many flowers, then little or no flowers are produced in the following year. In contrast, if the tree has no or hardly any flowers in a year, a relatively large amount of flower buds will be created in the following year. Among other determinants, it is because there is a limit to the biomass a tree can produce from the assimilates (i.e., energy sources) available through its metabolism (Friedrich et al. 2000).

1.3.3 Phenology Records

The BBCH[5] scale describes the unique growth stages of development of many cultivated plants. Figure 2 illustrates the visual transition between the different growth stages (Meier et al. 2009) that are most relevant for our analysis.

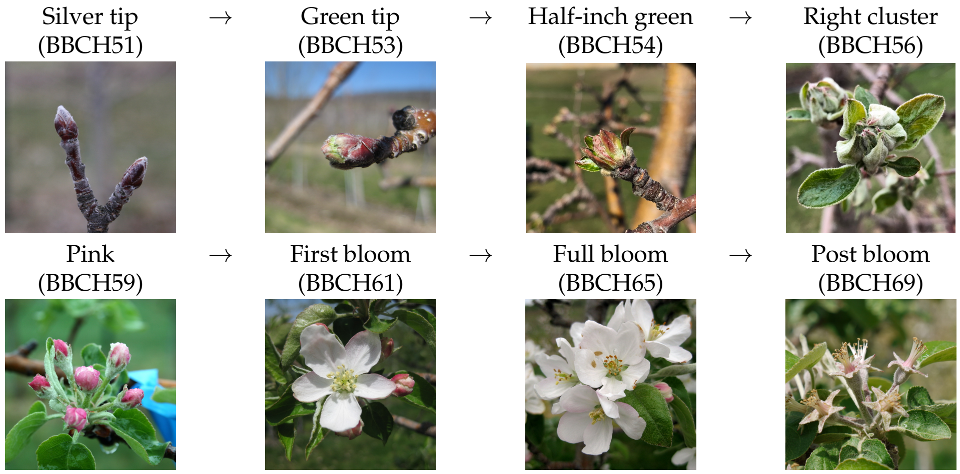
Apple phenology data was obtained by Agrometeo, an Agroscope project that contains information on the phenology and maturity of crops. This information is made available to Swiss producers free of charge on the website `www.agrometeo.ch`. The dataset contains variables on 22 measuring sites across ten cantons. It provides partial information on the BBCH development stages of 18 different apple varieties from 1997–2019. The data is gathered by farmers, who visit their fields regularly and record the developmental stages of the crops. Consequently, multiple dates may be associated with the same developmental stage for a particular station, variety, and year. This occurs because farmers tend to collect data more frequently than the actual transitions between growth stages. For example, a farmer might record observations twice during the BBCH53 stage, resulting in two separate dates being associated with that stage for a given year and location. In cases where multiple dates were recorded for the same stage, we kept only the earliest date, as this marks the point when the crop first reached that developmental stage.

Blooming dates, defined as the onset of BBCH65, vary from year to year. The data reveals both annual fluctuations and an overarching trend. We observe a negative trend, indicating that blooming dates have shifted to earlier dates over the years. Figure 14 in the Appendix illustrates the blooming dates for the most common apple varieties, as recorded in our orchard-level data, averaged across all measurement sites.

[4] We performed additional analyses by averaging data across varieties within each orchard, finding that model estimates for key climatic variables remained comparable. Phenology-dependent frost variables are negative and significant, though the negative impact of earlier spring frost events is less pronounced. Precipitation estimates are negative. The direction of the spline estimates for chill portions remains consistent, though the magnitude shifts slightly. The R-squared, AIC, and BIC values for the model using only a single variety per orchard were notably higher. The resulting predictions are presented in Figure 17 in the Appendix. Predictions remain robust across time horizons under RCP2.6 and RCP4.5. However, under RCP8.5, predictions start to diverge from the second time horizon onward, with variability across climate scenarios becoming much more distinct.

[5] The abbreviation BBCH derives from Biologische Bundesanstalt, Bundessortenamt and CHemical industry (Meier et al. 2009).

Figure 2: BBCH Stages

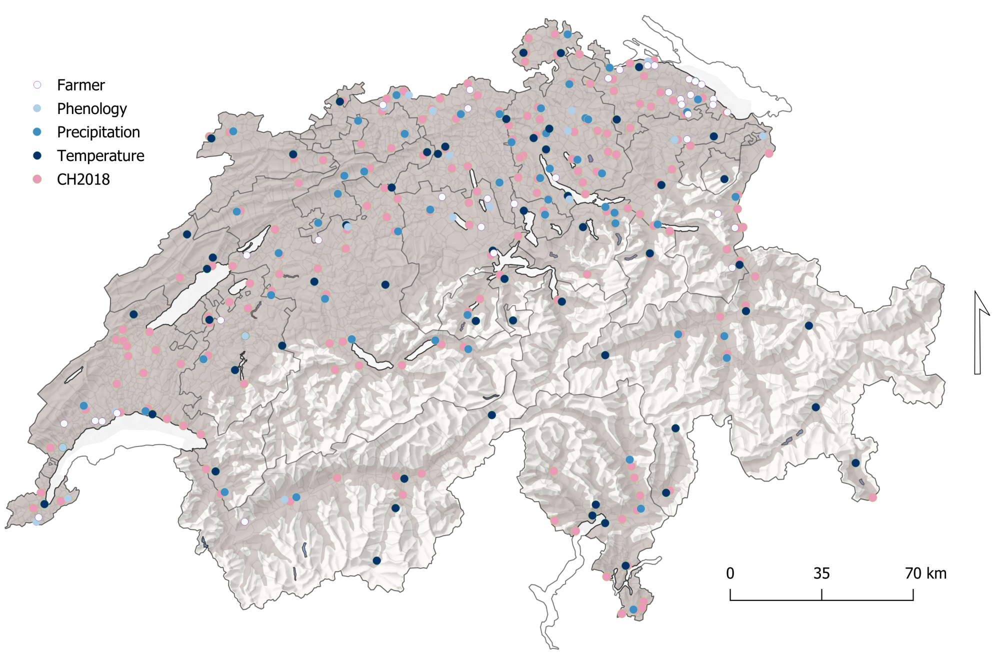


Notes: Phenological stages with corresponding BBCH numbers, ranging from silver tip to post-bloom.

1.3.4 *Station Selection*

The aforementioned stations were then geocoded using the Google Geocoding API, thereby assigning each station its corresponding latitude and longitude coordinates. Figure 3 illustrates the spatial distribution of these geocoded stations, encompassing various farms, temperature measurement sites, precipitation measurement sites, and phenology observation sites.

Figure 3: Geographical Locations



Notes: Map of temperature measuring stations, precipitation measuring stations, phenology measuring stations, farmers' locations, and the stations providing the CH2018 scenario data.

There are, in total, 192 stations providing scenario data, 37 unique farm locations, 22 phenology observing sites, 82 precipitation measurement stations, and 60 temperature measurement stations. Some of these stations may not be distinctly visible on the corresponding map due to spatial overlap. Specifically, 28 stations serve dual roles by collecting both temperature and precipitation data. The same subset also provides scenario data. There are 35 stations that overlap between temperature and scenario data collection, while 78 stations overlap between precipitation and scenario data collection.

To identify the nearest temperature and precipitation station for each farm, we implemented a function to compute the Vincenty distance, which accounts for the Earth's ellipsoidal shape, between a given farm location and all available weather stations. Subsequently, the weather dataset was constrained to include only the geographically closest stations. We did the same for the selection of stations of our 2018 scenario data. Table 6 in the Appendix lists all chosen stations.

1.4 Methods

We first carried out several data preparation processes to construct the necessary climate variables. Following this, we implemented and evaluated various models using out-of-sample selection techniques.

1.4.1 Data Preparation

Temperature Measurement Interpolation

We applied several transformations and adjustments to the temperature data. First, we interpolated the few missing temperature measurements. Among the over 140,000 daily temperature observations collected across various years and stations, 13 days of daily minimum and maximum temperature data were missing for station "GOE". Additionally, 15 days of daily minimum temperature and 17 days of daily maximum temperature data were missing for station "RAG". These gaps were closed through linear interpolation (Luedeling et al. 2013).

The PhenoFlex model for predicting blooming dates requires hourly temperature data as input. We employed daily temperature measurements to estimate hourly temperatures using a daily temperature curve, which applies a sine function for daytime warming and a logarithmic decay function for night-time cooling as described by Linvill (1990). The scenario data CH2018 has no missing values, so hourly temperature data was created without first having to interpolate linearly.

The PhenoFlex Model and BBCH Approximation

To predict the spring phenology of apple trees based solely on temperature, we use the PhenoFlex model (Luedeling et al. 2021). PhenoFlex is an integrated model combining the dynamic model for chill accumulation with the Growing-Degree-Hours (GDH) model for heat accumulation through a flexible transition. Luedeling et al. (2021) evaluated the predictive performance of PhenoFlex using 60 years of apple and pear data, comparing the results to benchmark models. Their findings indicated that PhenoFlex outperformed all other models, including the StepChill[6] model and a machine-learning approach. The most prominent driver of growth is temperature. There are two critical phases for the growth of the trees: the endodormancy (also called chilling) phase and the ecodormancy (also called forcing) phase. Trees need a sufficient amount of cooling in order to transition to the next phase where the biggest driver of growth is an accumulation of heat. The dynamic model is employed for chill accumulation in the endodormancy phase, followed by the GDH model for forcing. The transition between the two models is achieved using a sigmoid function, which effectively translates chilling into heat effectiveness. A critical chilling requirement, y_c, must be met for heat

[6] The StepChill model is a simplified version of the Unified model proposed by Chuine et al. (2016).

accumulation to begin. Below this threshold, heat does not accumulate; beyond it, heat becomes increasingly effective until it reaches full effectiveness. The end of heat accumulation is defined by z_c.

The model was calibrated using different combinations of chill and heat accumulation thresholds, while other model parameters were held constant. Calibration was performed using the aforementioned phenological measurements from Agrometeo. The average bloom date per variety over the years 1997–2019 was calculated (see Figure 14), selecting the three most prevalent varieties in the orchard-level data. "Gala" was chosen as the calibrating variety due to the smaller uncertainties in blooming dates and the availability of phenological measurements. The default values for the parameters y_c and z_c are $y_c = 40, z_c = 190$. The resulting bloom dates per station were averaged to obtain a measure of the average bloom date per year. These values were then compared with the actual average yearly bloom date of "Gala" from the measurement data. Over 6,300 different combinations of chill and heat parameters were tested within the intervals $y_c \in [25, 45]$ and $z_c \in [150, 450]$, minimizing the mean squared difference in days between the observed and the predicted bloom date. In addition, there were also some tests far outside the bounds of these intervals. The selected model with the resulting parameters being $y_c = 36$ and $z_c = 287$ exhibits the lowest error of 2.154 days.[7] Figure 4 presents the observed average bloom dates and the predicted bloom dates for the years 1997–2019.

Figure 4: Observed vs. Predicted Bloom Dates

Notes: Observed average bloom date (BBCH65) from the phenological data per variety over the years 1997–2019 and predicted average bloom date (BBCH65) using the calibrated model parameters.

We use PhenoFlex to predict the bloom dates for all selected temperature measurement stations (see Figure 15 in the Appendix) for both the past temperature data and the future scenario data. Based on the bloom predictions generated using PhenoFlex, we approximated the other phenological stages (BBCH). For this, we calculated the average temporal advancement among different BBCH stages using phenological measurements from Agrometeo. We selected the three largest varieties: Golden Delicious, Gala, and Braeburn. For each combination of station, variety, and BBCH stage, we determined the average number of days between stages. This dataset was then summarized to calculate the average day differences across all stations for each variety and BBCH stage. Finally, the overall average day difference for each BBCH stage was calculated across all varieties. This approximation provided the 'time between phenological stages' for the following BBCH stages: 51, 53, 54, 56, 57, 59, 61, 65, and 69. Based on the approximated phenological stages we created phenology-specific frost variables, as susceptibility to frost varies according to phenology. Based on chamber studies, critical temperatures were identified below which at least 10% of the flowers are killed. These numbers are based on the FAO report on frost protection (Snyder and Melo-Abreu 2005).

[7] Square root of 4.6397 days^2

Table 2: Critical Frost Temperatures

BBCH	**Stage**	**Critical Temp T_c**
51	Silver tip	-11.9 °C
53	Green Tip	-7.5 °C
54	Half-inch green	-5.6 °C
56	Cluster	-3.9 °C
57	Pink bud	-2.8 °C
59	Pink ball	-2.7 °C
61	First bloom	-2.3 °C
65	Full bloom	-2.9 °C
69	Post bloom	-1.9 °C

Notes: Critical frost temperatures T_c, below which at least 10% of the flowers are killed, corresponding to the BBCH stages mentioned before. The numbers are based on the FAO report on frost protection (Snyder and Melo-Abreu 2005).

Chilling models and growing degree hours

In addition, we created different measures for the capturing of chill units and growing degree hours. We created chilling hours according to the Weinberger model (aka Chilling Hours model) (Weinberger et al. 1950; Bennett et al. 1949), chill units based on the Utah model, as suggested by Richardson et al. (1974) and chill portions according to Fishman (Fishman et al. 1987a,b). In the Weinberger model, temperatures between 0°C and 7.2°C have a cooling effect and each hour within that interval is counted as one chilling hour. Chilling hours are then summed up during the dormant season. Warm temperatures, however, can negatively impact chill accumulation. This insight led to the development of the Utah model, which assigns differential weights to various temperature ranges (Richardson et al. 1974). Every hour within the 1.4°C to 12.4°C range contributes variably to chill accumulation based on temperature. For instance, an hour at 1.5–2.4°C contributes 0.5 chill units, while an hour at 2.5–9.1°C contributes one chill unit. Additionally, the Utah model accounts for the negative impact of higher temperatures by incorporating negative chill units, such as subtracting 0.5 chill units for each hour at 16–18°C. The third common modeling approach is the Dynamic model, developed by Fishman et al. (1987a,b). This model proposes that chill accumulates through a two-step process. In the first step, an intermediate chill product is formed. This product is produced most efficiently at low temperatures. But this process is reversible, as this intermediate chill product can be destroyed by heat. However, when exposed to moderate temperatures, this intermediate product undergoes a transformation, which is then irreversible, into a chill portion. Chill portions accumulate and contribute to fulfilling chilling requirements. The Dynamic model accounts for the negative impact of high temperatures, the limit to how much chill can be reversed, and the chill-enhancing effect of moderate temperatures when cycled with cooler conditions. A significant distinction of the Dynamic model from earlier approaches is the emphasis on the sequence of temperatures during the cold season. Unlike the Chilling Hours model and Utah model, where similar temperatures have the same effect regardless of timing, the Dynamic model considers the interaction of multiple processes. The production of a chill portion depends on the presence of a certain quantity of the intermediate product, leading to varying effects of similar temperatures at different times in the season on chill accumulation (Luedeling 2012).

In addition to the three different chill indicators, chilling hours, chill units, and chilling portions, we created growing degree hours (GDH) according to Anderson et al. (1986), using the default values they suggest. The calculation of the GDH was as follows:

$$\mathrm{GHD} = \frac{\mathrm{FA}}{2}\left\{1 + \cos\left[\pi + \pi(\mathrm{TH} - \mathrm{TB})(\mathrm{TU} - \mathrm{TB})\right]\right\}$$

where:

$$\begin{aligned}
\mathrm{TH} &= \text{the hourly temperature}\\
\mathrm{TB} &= \text{the base temperature } (4^{\circ}\mathrm{C} \text{ for fruit trees})\\
\mathrm{TU} &= \text{the optimum temperature } (25^{\circ}\mathrm{C} \text{ for fruit trees})\\
\mathrm{TC} &= \text{the critical temperature } (36^{\circ}\mathrm{C} \text{ for fruit trees})\\
\mathrm{A} &= \mathrm{TU} - \mathrm{TB} \text{ (the amplitude of the growth curve) and}\\
\mathrm{F} &= \text{a stress factor which can be used to represent various forms of plant stress}
\end{aligned}$$

The different winter chill indicators, as well as the growing degree hours, were created for both the past hourly temperature data and the future hourly scenario data.

Other Climatic Variables and Data Combination

To better capture the underlying relationship between the climate impact and the agricultural yield, additional climatic variables on the basis of the growing season were built. As a control measure, a basic frost indicator was established, defined as the incidence of minimum temperatures falling below 0°C. Furthermore, we calculated growing degree days, which are a modification of the daily mean temperature (T). The construction thereof is suggested in the agronomic as well as in the economic literature (e.g., Schlenker et al. 2006; Deschênes and Greenstone 2007; D'Agostino and Schlenker 2016), since they capture beneficial heat. Apple growing degree days were formed by taking the difference of the daily mean temperature to a lower threshold of 5°C for each day and then aggregating it over the growing season.

$$\mathrm{DD5(T)} = \begin{cases} 0 & \text{if } \mathrm{T} \leq 5 \\ \mathrm{T} - 5 & \text{if } 5 < \mathrm{T} \leq 30 \\ 25 & \text{if } \mathrm{T} > 30 \end{cases}$$

For example, a day with a mean temperature of 12°C would account for seven growing degree days. If the temperature is below 5°C, the day is not counted, resulting in zero degree days. We imposed an upper bound to the growing degree days at 30°C, where days with a higher temperature each count the maximum of 25 growing degree days. In addition, hot degree days were created to capture the impact of heat stress (> 30°C). As heavy rainfall can damage crops, three different precipitation indicators were built. MeteoSwiss categorizes precipitation from 10–30 mm over 24 hours as high, 30–50 mm as very high, and >50 as profuse.[8] The daily precipitation data, however, does not allow us to distinguish whether the 50 mm fell over one, five, or 24 hours.

Agricultural outcomes are reported on an annual basis. Hence, the weather data has to be aggregated over the same time scale. The standard approach is to sum weather variables across all days of the growing season (Blanc and Schlenker 2020). In line with the standard approach, the weather data, including the created climate indicator, was

[8] www.meteoswiss.admin.ch/weather/weather-and-climate-from-a-to-z/precipitation.html

summed over the growing season for individual years for each station to create yearly data. The yearly temperature, phenological, and precipitation indicators were then merged with the orchard-level dataset according to the geographically closest location.

1.4.2 *Statistical Model*

Climate impacts on agriculture are increasingly relying on panel models. Blanc and Schlenker (2020) point out several advantages of panel models compared to cross-sectional models and other types of models. First of all, panel models have the ability to uncover causal relationships and provide more degrees of freedom allowing out-of-sample forecasts for model validation. Furthermore, they allow the use of fixed effects that will absorb all time-invariant confounding variation and account for omitted variables. They can also account for short-term adaptation. On the other hand, there are some limitations to this approach. One concern is the source of variation: for sufficiently small climate changes, panel variation yields the correct effect, while the relationship revealed by non-marginal climate changes (global warming) may be inaccurate. As opposed to short-term adaptation, panel models inaccurately deal with long-term adaptation, assuming the relationship between yields and weather remains unchanged as the climate changes (Blanc and Schlenker 2020). If adaptation plays a significant role, the impact of yearly fluctuations is an insufficient proxy for climate change. However, this concern is mitigated when studying perennial crops, as farmers managing these crops tend to exhibit more path-dependent behaviors compared to those dealing with annual crops. Nevertheless, this limitation cannot be fully addressed within the current model. Another possible concern is measurement errors and homogeneity effects across seasons. Measurement errors can occur because weather is measured at the station level and must be spatially interpolated to match regional/national agricultural data. In addition, agricultural data and weather data are reported on different time scales, where weather data has to be aggregated to yearly data.

We estimate the effect of frost events and other climate variables on orchard-level apple yield per hectare using panel data and quantify the effect using the following general model:

$$Y_{it} = X_{it}'\beta + z_t'\delta + c_i + \epsilon_{it}, \quad i = 1, ..., n \quad t = 1, ..., T$$

Y_{it} denotes the dependent variable, orchard-level apple yield (kg/ha). They are observed for each orchard i and each year t and X_{it} is the regressor matrix that contains all the independent climate variables. We use different specifications and then choose the most appropriate model in terms of prediction capability. Orchard fixed effects (c_i) are included. These group fixed effects will absorb any confounding effect caused by unobserved factors that are constant over time within each group. Including group fixed effects will jointly demean the dependent and independent variables. This will transform weather variables into weather shocks, as they will be deviations from the mean (Blanc and Schlenker 2020). Variation over time in X_{it} is needed to estimate β consistently. We include a quadratic year trend (z_t), as year-fixed effects absorb most of the variation. Given that the error terms are likely heteroskedastic and correlated in the group dimension, we apply orchard-clustered heteroskedasticity-robust standard errors.

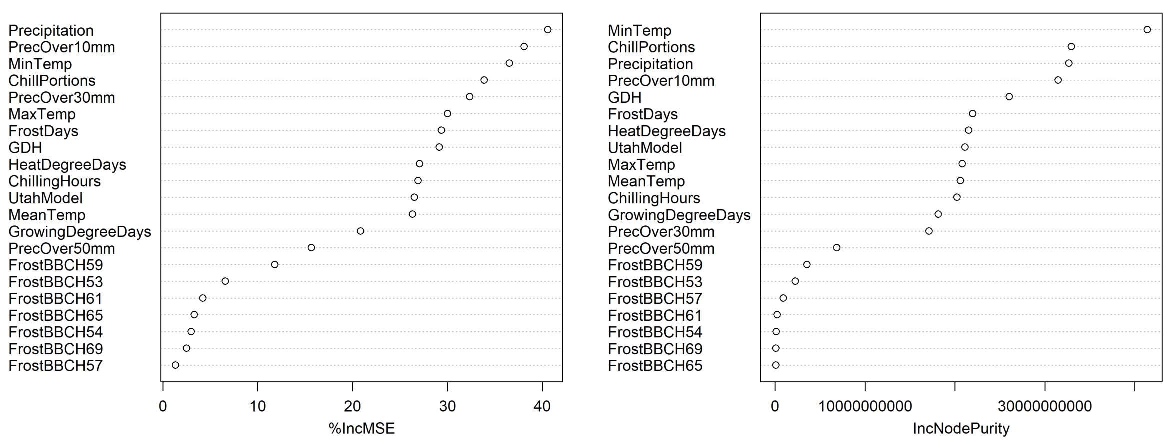
Model Selection

We built several models to capture the underlying relationships between climate variables and crop yield. Focusing on the impact of different frost and chilling conditions, we chose a standard baseline model to control for other variables. Temperature effects were incorporated through growing degree days, while we accounted for heat stress by introducing the heat degree variable. Precipitation variables, including squared precipitation, were also included as well as a quadratic time trend to capture technological change. To address biennial bearing effects linked to frost events, we included a one-year lag of the spring frost variable. We estimated frost effects in the baseline model using all our phenology-dependent variables. Further, we used a spline of chill portions using four degrees of freedom. We focused on chill portions, as the dynamic model is more complex and the use thereof is recommended (Luedeling 2012).

First, we incorporated various chill model combinations. We estimated the model using the chilling hours and chill portions, as well as the chill units from the Utah model and chill portions, as the Utah model was built on the chilling hours model and should, therefore, be substitutable. Next, we tested different combinations of phenology-dependent frost variables using the baseline model, including the spline of chill portions. As we are able to most accurately predict the time of full bloom, we estimated the model just using spring frost at full bloom. We also estimated a model including our simplest frost measure, as previously described. These different combinations led to models M1 through M5.

In addition to this bio-physical approach, we constructed a model that incorporates variable selection using random forests (RF) (Genuer et al. 2010). There is a growing research literature on the estimation and prediction of crop yields using RF algorithms (Prasad et al. 2021). The random forest algorithm ranks explanatory variables based on their importance scores. As an ensemble learning method for classification and regression, random forests build multiple decision trees using bootstrapped samples, combining their predictions to enhance accuracy. Variable importance in RF measures how much each feature contributes to model accuracy.

Figure 5: Variable Importance using RF



Notes: Quantification of variable importance using RF. On the left is the permutation-based importance, and on the right is the impurity-based importance.

Two primary measures were used to assess variable importance (VI), see Figure 5. The left panel presents the permutation-based importance. For each tree, the prediction error, mean squared error (MSE), on the out-of-bag (OOB) data is recorded. Then, the same process is repeated after permuting each predictor variable. Through permutations, the relationship to the target variable is broken, helping to assess the importance of this variable. The difference between the original and permuted prediction errors is averaged across all trees and normalized by the standard deviation of the differences. The right panel of Figure 5 illustrates the impurity-based importance. In decision trees, data is split at different nodes based on specific features. This is done to make the data more homogeneous with respect to the target variable. A variable is considered important if it consistently helps to split the data in a way that reduces impurity (i.e., improves predictions). Impurity is measured by the residual sum of squares, the difference between the predicted and actual values. However, as noted in the literature, the impurity-based importance measure is often biased (Gregorutti et al. 2017). We included the ranking here for completeness but dropped the variables lower than 20% focusing on the permutation-based importance measure.[9] The regression results for this model can be found in M6.

[9] As can be seen in Figure 5, the results would not change if we focused on the impurity-based importance instead. The eight least important variables are identical for both the permutation-based and the impurity-based importance measure.

As an additional control, we also applied a step-wise model selection, a modified version of the backward variable elimination procedure as described by Fox et al. (2017). In the first step, the full model is estimated on the training set (70% of the data), and the performance of the model is measured using the root-mean-squared error (RMSE) of their predictions on the test set (30%). All predictors are ranked according to their VI. In the next step, the variable with the lowest VI is dropped from the sample, and the model is estimated again. This process is repeated until there are no variables left. The model with the lowest RMSE is chosen. This led to model M7.

To select and validate our best model, we examine the RMSE of out-of-sample predictions, as well as the Akaike information criterion (AIC) and Bayesian information criterion (BIC). AIC and BIC are commonly used model selection criteria: AIC is better suited for prediction-focused models, while BIC is preferable when the goal is to identify the correct model (Chakrabarti and Ghosh 2011).

Table 3: Selection Criteria

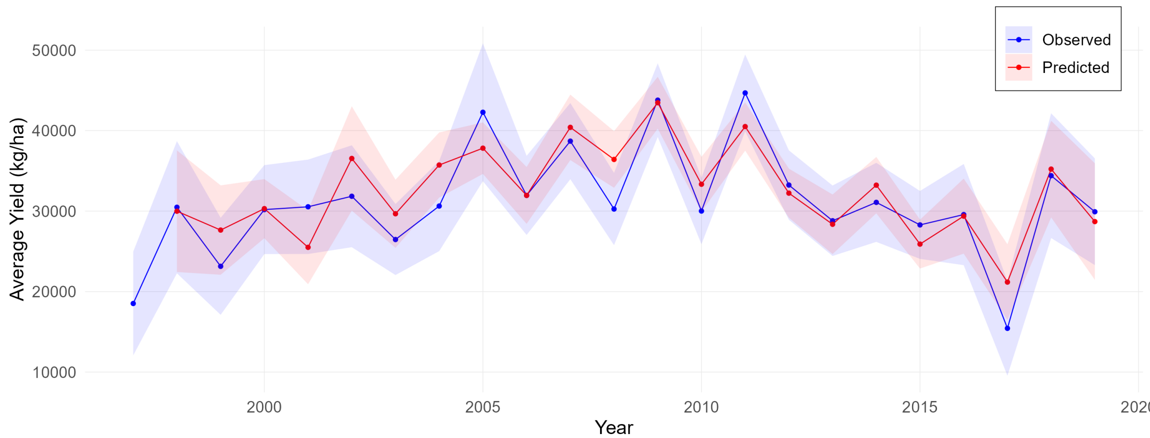
Model	RMSE (70/30 split)	RMSE (Year split)	AIC	BIC
M1	11 225.33	11 275.85	48 064.24	50 325.64
M2	11 335.96	11 445.93	48 106.58	50 356.58
M3	11 229.30	11 300.56	48 069.22	50 319.22
M4	11 693.57	11 854.44	48 231.79	50 441.92
M5	11 722.81	11 882.03	48 240.87	50 451.00
M6	12 114.35	12 098.20	58 128.72	60 809.85
M7	12 393.28	12 433.79	58 235.71	60 893.32

Notes: Model comparison showing RMSE from the out-of-sample predictions using the 70% training set/30% test set split and the year split, alongside AIC and BIC values.

We calculated the RMSE for out-of-sample predictions using two different approaches. First, we divided the data into a training set (70% of the data) and a test set (30%). The model is then run on the training set with the estimated parameters used to predict yield in the test set. The RMSE is computed by comparing the actual yield values with the predicted yield values from the test set. This process was repeated 50 times, and RMSE values were averaged.[10] Table 3 presents the root-mean-squared error (RMSE) of the out-of-sample predictions over the 50 repetitions alongside the AIC and BIC for each model. Second, we split the data along the time dimension. The regression models were run on data from the years 1997 to 2017 and then used to predict yields for 2018 and 2019. The RMSE was calculated by comparing the actual yields from these years with the predicted values. In the next step, we randomly took out single years, ran the regression model on the sample of remaining years, and then predicted the left-out year. We then averaged the RMSE over each year's prediction; see again Table 3. In both our metrics, M1 outperforms all other models based on the RMSE. It is also the model with the lowest AIC. As mentioned before, AIC is better suited for prediction-focused models compared to BIC. Based on these considerations, we opted to proceed with M1. Models including phenology-dependent frost measurements consistently outperformed those limited to frost around full bloom or a simplified frost model. Furthermore, models built on biophysical relationships outperformed those using random forest variable selection.

[10]The results are robust to repeating the process 5000 times.

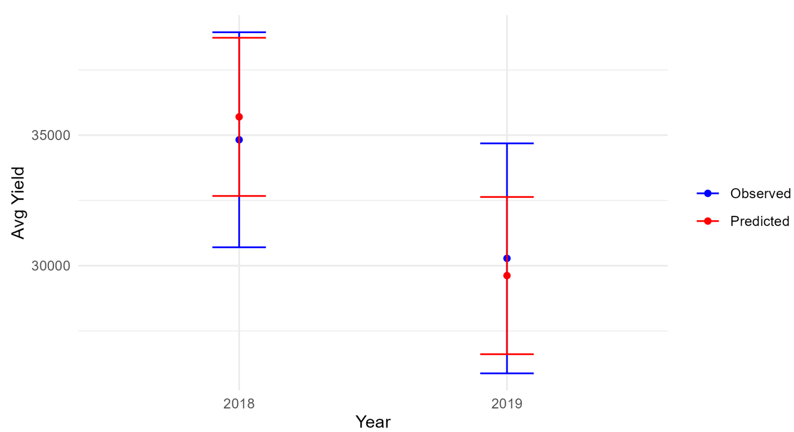
Figure 6: Out-of-sample Predictions (70/30 Split)



Notes: Out-of-sample predictions generated using the selected model with a 70/30 data split. The regression model was trained on 70% of the data and used to predict the average yield over time for the remaining 30%. The plot displays the predicted yield (kg/ha) alongside the actual yield (kg/ha) for the 30% test data.

Figure 6 illustrates the out-of-sample predictions produced by M1. This model was trained using 70% of the data, and the estimated parameters were subsequently applied to predict the average yield on the remaining 30%. Due to the inclusion of a lagged frost variable in the model, the first prediction begins one year after the observed yield data. Figure 7 presents the performance of additional out-of-sample predictions, where we split the dataset into the years 1997–2017 and then predicted both the years 2018 and 2019. Furthermore, Figure 16 in the Appendix displays the observed and predicted yields for all years, predicting each year as an individual out-of-sample prediction.

Figure 7: Out-of-sample Predictions (Year Split)



Notes: Out-of-sample predictions were generated using the selected model, with the data split into the years 1997–2017 for training and predictions made for the years 2018 and 2019. The predicted yield (kg/ha) is compared to the actual yield (kg/ha) for these years.

Table 4: Regression Outputs

Dependent Variable:	Yield (kg/ha)						
Model:	(M1)	(M2)	(M3)	(M4)	(M5)	(M6)	(M7)
GDD	22.56***	12.85**	18.20***	20.07***	21.68***	62.72***	
	(4.786)	(5.322)	(4.034)	(4.958)	(4.837)	(11.04)	
HDD	-381.2***	-285.2***	-198.3***	-426.7***	-456.8***	-188.1**	-143.3**
	(47.79)	(59.76)	(55.28)	(49.38)	(57.71)	(86.31)	(65.47)
Precipitation	9.559	1.167	-6.819	14.19	14.64	-9.216*	-11.92***
	(19.36)	(20.12)	(19.16)	(19.79)	(19.59)	(5.078)	(3.957)
Precipitation^2	-0.0101	-0.0054	-0.0017	-0.0121	-0.0122		
	(0.0089)	(0.0092)	(0.0088)	(0.0091)	(0.0090)		
Frost BBCH53	-7,699.4***	-7,750.1***	-7,855.4***				
	(1,668.8)	(1,718.4)	(1,777.6)				
Frost BBCH54	-4,882.4***	-5,204.2***	-5,613.3***				
	(1,420.0)	(1,466.7)	(1,444.4)				
Frost BBCH57	-3,500.8***	-4,984.9***	-4,744.3***				
	(833.2)	(852.7)	(852.8)				
Frost BBCH59	-5,588.7***	-4,776.3***	-4,378.4***				
	(1,014.4)	(1,033.7)	(1,055.1)				
Frost BBCH65	-28,242.3**	-28,045.1**	-27,828.8**	-26,485.6**			
	(10,987.9)	(10,922.1)	(10,888.0)	(10,719.8)			
Frost BBCH69	-8,600.6***	-8,833.5***	-9,383.1***				
	(2,662.2)	(2,560.7)	(2,490.6)				
Frost$_{t-1}$	24.81	-20.42	-64.15	33.30	46.39		
	(42.04)	(44.28)	(43.97)	(43.68)	(47.62)		
Spline(Chill portions)[1]	-5,618.7***			-6,125.6***	-5,689.8***		
	(2,058.1)			(2,022.2)	(2,002.0)		
Spline(Chill portions)[2]	-13,411.9***			-13,381.6***	-12,746.8***		
	(1,805.7)			(1,800.3)	(1,966.7)		
Spline(Chill portions)[3]	-21,192.3***			-23,647.5***	-22,954.8***		
	(4,552.7)			(4,252.6)	(4,768.5)		
Spline(Chill portions)[4]	6,142.9**			7,122.7***	7,654.2***		
	(2,546.8)			(2,616.8)	(2,893.1)		
Year	33,416.5	17,449.8	7,360.0	51,565.6	57,874.7		
	(71,082.5)	(70,499.3)	(70,164.2)	(68,915.1)	(69,609.7)		
Year^2	-8.096	-4.143	-1.625	-12.62	-14.19		
	(17.69)	(17.54)	(17.46)	(17.14)	(17.32)		
Chilling hours		5.617**				3.893	9.543***
		(2.194)				(2.646)	(2.518)
Chill portions		-320.6***	-535.1***			-533.6***	-377.8***
		(78.56)	(83.18)			(94.18)	(57.51)
Utah model			9.189***			17.68***	
			(1.492)			(2.393)	
Frost days					31.64	156.8*	3.280
					(52.47)	(88.94)	(52.00)
Precipitation (10mm)						65.11	156.1*
						(91.18)	(82.12)
Precipitation (30mm)						-389.6	
						(240.7)	
GDH						0.2518	
						(0.2429)	
Tmin						81.65***	14.85**
						(13.28)	(6.502)
Tmax						66.93***	15.06**
						(13.52)	(6.769)
Tmean						-183.0***	-31.76***
						(29.98)	(6.508)
Orchard Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,200	2,200	2,200	2,200	2,200	2,643	2,643
R^2	0.58340	0.57453	0.58169	0.56223	0.55958	0.53139	0.51055
Within R^2	0.17407	0.15649	0.17070	0.13211	0.12686	0.09998	0.05996

Clustered (orchard) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4 presents the regression results for all models. In M1, estimates indicate a significant positive non-linear effect of temperature, which is captured by the growing degree days variable. As expected, days with maximum temperatures exceeding 30°C have a significant negative effect on yield. Coefficients for precipitation estimate a small positive effect with a negative second-order term, however, neither effect is statistically significant. The effects of our phenology-dependent variables are all negative and significant. Frost during full flowering (BBCH65) has the largest significant negative effect on yield. Given an average yield of approximately 30,000 kg/ha, a severe frost event occurring at full bloom could result in near-total harvest loss. The lagged frost variable shows a positive coefficient, which aligns with the expected relationship. Among chill models, chilling hours have a positive effect on yield, while chill portions show a negative effect.

The three models demonstrating the best predictive performance are M1, M3, and M2. Phenology-dependent variables remain negative and significant, displaying consistent effect sizes and significance across models. The non-linear impact of chill portions, captured by the spline function, is also significant. The lagged frost variable is positive, as expected in M1, M4, and M5, and negative in M2 and M3 indicating a potential interaction with chill portions.

1.5 Scenario Analysis

For the scenario analyses, we used the relationships estimated from our panel model based on historical climate data from 1997 to 2019. We then built projections of the impact of different climate scenarios and emission pathways on yield for the years 2025 to 2099.

1.5.1 Climate Change Scenarios CH2018

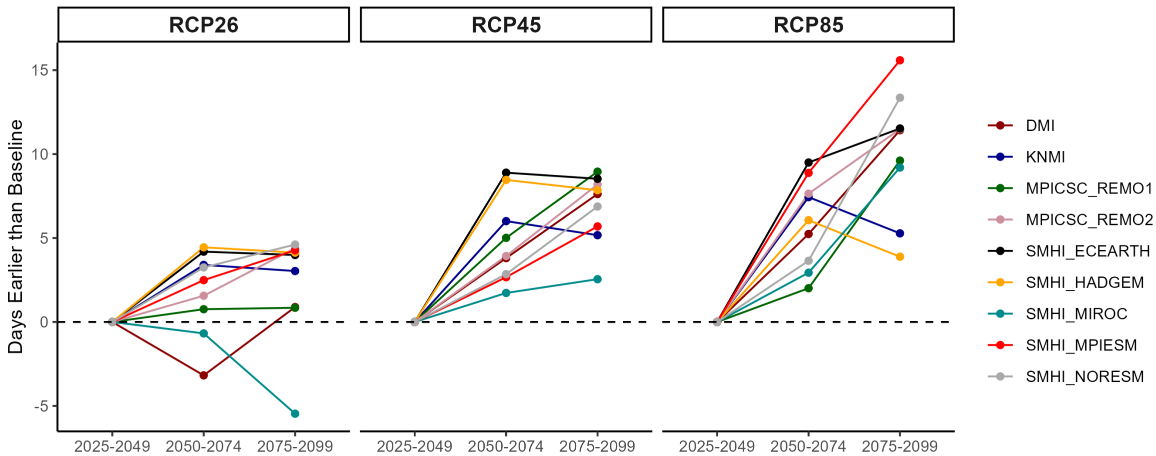
For our scenario data, we used the Climate Change Scenarios from MeteoSwiss, i.e., the localized CH2018 datasets. This dataset provides transient daily time series for the period 1981–2099 for several Swiss stations and for several climate variables. The Swiss climate scenario CH2018 are projections derived from the EURO-CODEX ensemble of climate change simulations with different combinations of global (GCMs) and regional climate models (RCMs). RCMs are most advantageous in regions with complex topography such as Switzerland. EURO-CORDEX involves more than 30 European modeling centers, applying more than 10 different RCMs on a pan-European model domain (CH2018 2018).

The daily time series were generated using a statistical bias-correction and downscaling method to the original output of all EURO-CORDEX climate model simulations. It includes 68 simulations, of which a subsample will be used for this analysis. Some of these 68 simulations show problematic values, such as unrealistic snow accumulations in the Alps. The simulations are conditioned on different Representative Concentration Pathways (RCPs). The three RCPs, RCP8.5, RCP4.5, and RCP2.6, are different scenarios of anthropogenic forcing (greenhouse gases, aerosols, and land use). They can be understood as emission scenarios. They imply a range between a significant reduction of global emissions (RCP2.6) and growth of emissions that continues until the end of the century (RCP8.5). For each RCP, four climate variables are available: minimum temperature, maximum temperature, mean temperature, and precipitation. These scenarios cover 37 different stations in Switzerland. Out of the 68 available, we selected the nine simulations for which all RCPs are available. They are a representation of different RCMs, GCMs, and spatial resolutions.[11]

We then restricted the dataset to the years 2025–2099 and limited the set of stations to those below 700 meters above sea level. Next, we transformed the daily measurements into hourly temperature data, which were then used to predict blooming dates, chill indicators, and growing degree hours.

[11] The nine chosen simulations are the following: DMI-HIRHAM-ECEARTH-EUR11 (DMI), KNMI-RACMO-HADGEM-EUR44 (KNMI), MPICSC-REMO1-MPIESM-EUR11 (MPICSC), MPICSC-REMO2-MPIESM-EUR11 (MPICSC2), SMHI-RCA-ECEARTH-EUR11 (SMHI ECEARTH), SMHI-RCA-HADGEM-EUR44 (SMHI HADGEM), SMHI-RCA-MIROC-EUR44 (SMHI MIROC), SMHI-RCA-MPIESM-EUR44 (SMHI MPIESM), SMHI-RCA-NORESM-EUR44 (SMHI NORESM)

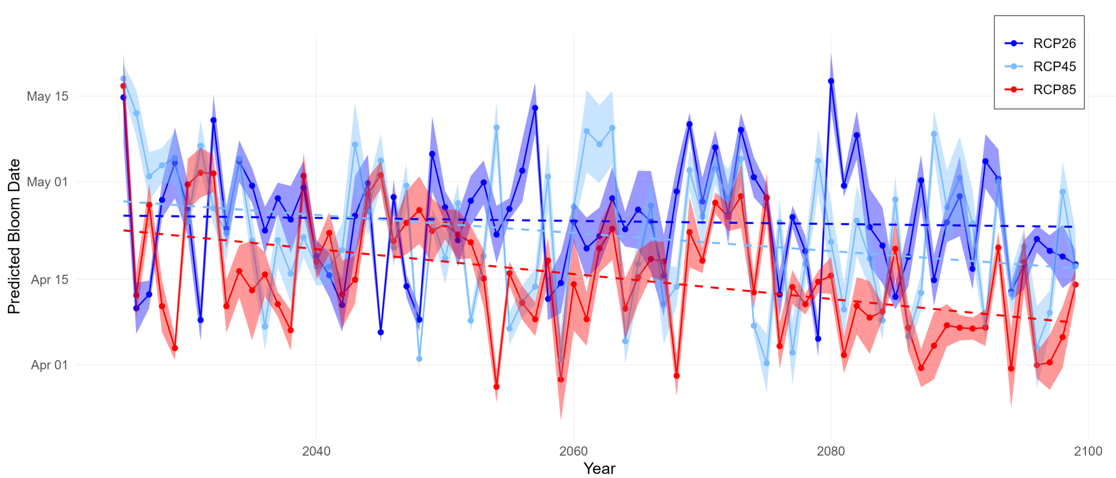
Figure 8: Bloom Stages across Scenarios



Notes: Development of full bloom stage BBCH65 across various climate change scenarios, emission scenarios, and time horizons. Positive values on the y-axis indicate days the full bloom occurs earlier (e.g., a value of 5 means full bloom occurs 5 days earlier on average), while negative values indicate a shift to a later bloom date.

Full bloom generally shifts to earlier dates across time horizons, RCP scenarios, and climate models. Higher emission scenarios and projections further into the future predict an increasingly earlier occurrence of the full bloom stage (BBCH65). Specifically, under RCP8.5 around 2075–2099, full bloom is predicted to occur on average up to 15 days earlier. Figure 8 presents the development of bloom stages compared to the period 2025–2049. We already observe variability across climate scenarios; while the overall trend is evident, individual scenario predictions show a considerable spread.

Figure 9: Predicted Bloom Dates – DMI

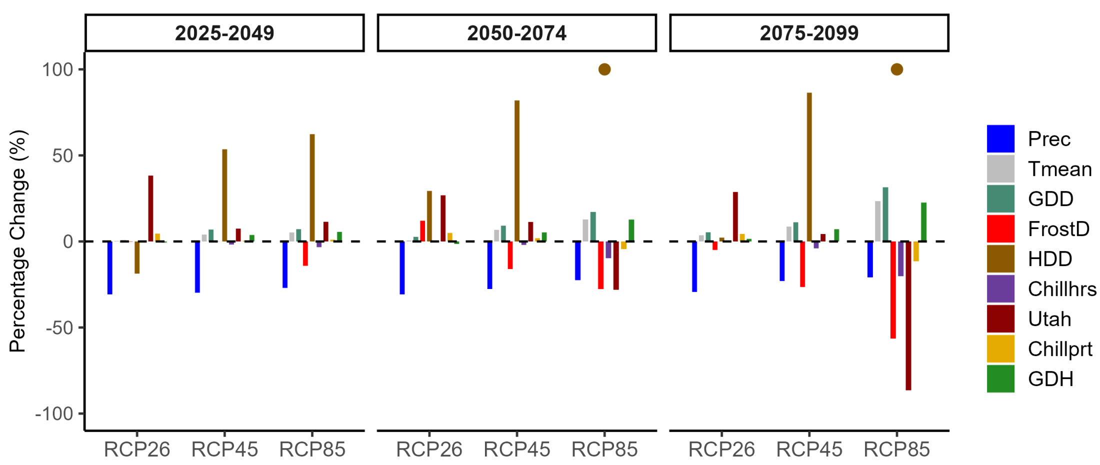


Notes: Average predicted bloom date (BBCH65) across temperature measurement sites from 2025 to 2099 for three different RCP scenarios of the DMI climate model, modeled using PhenoFlex.

Exemplary, Figure 9 illustrates the predicted bloom dates (BBCH65), averaged across all temperature measurement sites derived from the DMI climate model. Bloom dates are modeled for each RCP for the years 2025–2099. The trend lines indicate that under RCP2.6, the bloom dates remain stable on average, moving from the beginning to the end of the century. RCPs 4.5 and 8.5, on the other hand, show a negative trend which means that the flowering period occurs earlier over time.

We calculated changes in climate variables across all climate scenarios, RCPs, and time horizons, using the historical period 1997–2019 as the baseline. Percentage changes for all climate variables, excluding phenology-dependent frost days, are presented in Tables 7 and 8 in the Appendix. Absolute changes in phenology-dependent frost variables are provided in Tables 9 and 10. Additional summary statistics for all climate variables, based on nine different simulations, can be found in Tables 11 to 13 in the Appendix. The timeline is divided into three periods: 2025–2049, 2050–2074, and 2075–2099. Notably, several climate trends emerge. Average temperatures increase across all scenarios, with the rate of increase intensifying over time and across emission scenarios. This trend is consistent for all three temperature indicators: mean temperature (Tmean), growing degree days (GDD), and growing degree hours (GDH). Additionally, extreme heat events, measured by heat degree days (HDD), are projected to occur more often. Some scenarios, such as MPICSC and MPICSC2, display a more moderate rise in heat degree days compared to others, while SMHI HADGEM, KNMI, SMHI ECEARTH, and SMI MPIESM show the highest increase. Frost days generally decrease across scenarios, with more pronounced reductions under emission scenario RCP8.5, whereas phenology-dependent frost days increase relative to the reference period but decrease over later time horizons and higher RCPs. Certain scenarios predict an initial rise in frost days, followed by a decline in subsequent periods, with very few phenology-specific frost days occurring overall. For the chill indicators – chill hours (Chillhrs), the Utah model (Utah), and chill portions (Chillprt) – distinct patterns emerge over time. Summary statistics in Tables 11 to 13 show a general decline beginning in the 2025–2049 period, with the most significant reduction under RCP8.5. Percentage changes from the reference period reveal considerable volatility in these variables over time. Precipitation, on average, decreases relative to the reference period; however, no consistent trend appears across RCPs, time horizons, or climate scenarios. In some cases, precipitation increases under RCP2.6 and decreases under RCP8.5, while the reverse trend is seen in other scenarios, underscoring the considerable uncertainty in the temporal development of precipitation.

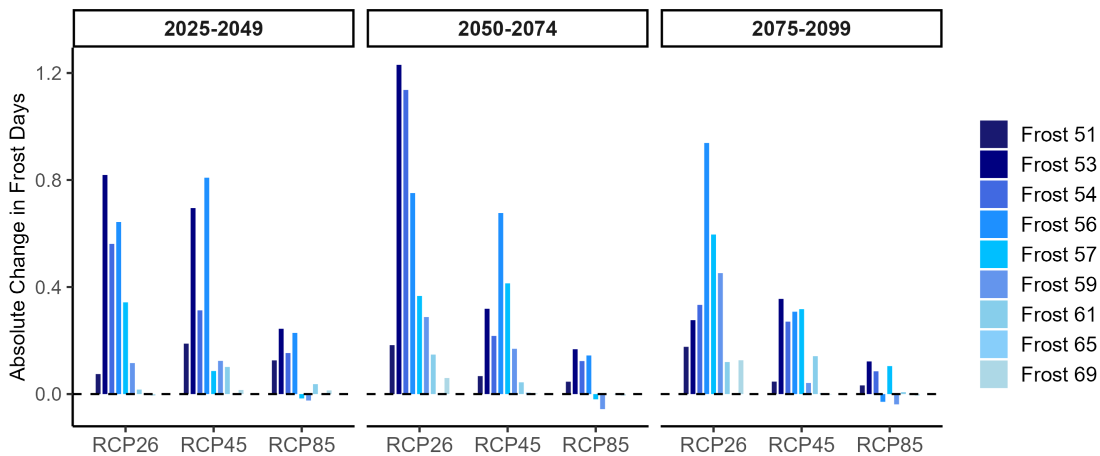
Figure 10: Climate Variables Percentage Changes – DMI



Notes: Projected percentage changes in climate variables relative to the historical baseline period (1999–2019) for three future time horizons (2025–2049, 2050–2074, 2075–2099) under three emissions scenarios (RCP2.6, RCP4.5, and RCP8.5), based on the DMI climate model projections.

Exemplary, Figure 10 illustrates the percentage changes of the climate variables for climate scenario DMI, relative to the baseline period, over the different time horizons and emission scenarios. There is a steep increase in heat degree days. For RCP8.5 for the time horizons 2050–2074 and 2075–2099 we observe a percentage increase larger than 100 percent, visualized by a dot at 100 percent, in order to maintain a better visibility of the percentage changes of the other variables. Similarly, Figure 11 presents the absolute changes in frost variables relative to the baseline period. In general, only a limited number of phenology-dependent frost days were observed during the baseline period, with few frost days per phenological stage across the climate change scenarios. Notably, the RCP8.5 scenario shows a lower number of frost days compared to RCP2.6. Even when accounting for an earlier shift in the date of full bloom, a clear reduction in frost days is evident across emission scenarios, suggesting a beneficial impact on yield.

Figure 11: Changes in Frost Variables – DMI



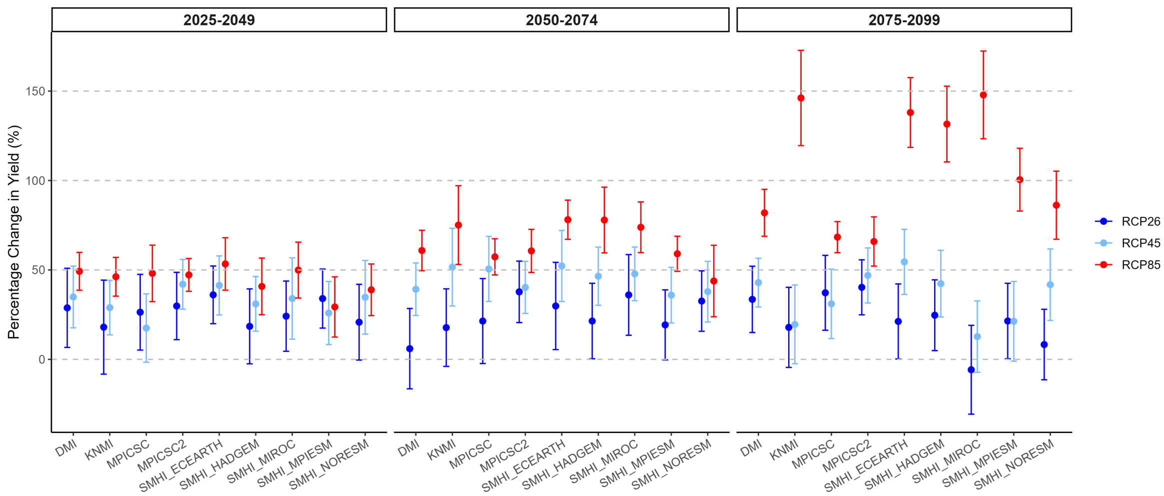
Notes: Projected absolute changes in frost variables relative to the historical baseline period (1999–2019) for three future time horizons (2025–2049, 2050–2074, 2075–2099) under three emissions scenarios (RCP2.6, RCP4.5, and RCP8.5), based on the DMI climate model projections.

1.5.2 Model-Based Yield Projections

We applied the estimated relationship from the panel model, derived from climate data from 1997 to 2019, to predict the impact of future climate conditions on crop yield under various climate scenarios and emission pathways for the period 2025 to 2099. We excluded the year trend, to isolate the effects of climate variables from temporal trends, and did not allow for negative future yield. To assess the relative change in yield, we calculated the percentage change from a historical reference yield, which was determined as the average yield for each orchard from 1997 to 2019. We then generated annual yield estimates for each orchard across the projected time horizon and calculated the annual percentage change in yield for each orchard.

To summarize the results, we aggregated the average percentage change in yield across three distinct time periods within the projection window. Additionally, we computed confidence intervals for these estimates to assess the uncertainty associated with the projections. This approach enabled us to examine how projected yield changes vary across different future time periods and climate scenarios. Figure 12 presents the percentage change in yield relative to the reference yield across all nine climate scenarios under three RCPs for the three distinct time horizons. The figure displays the mean percentage change in yield alongside the corresponding 95% confidence intervals (CI). The CIs are indicative of uncertainty in the mean percentage change in yield, coming from year-to-year variability and variability in yield across orchards.

Figure 12: Percentage Changes in Yield – M1

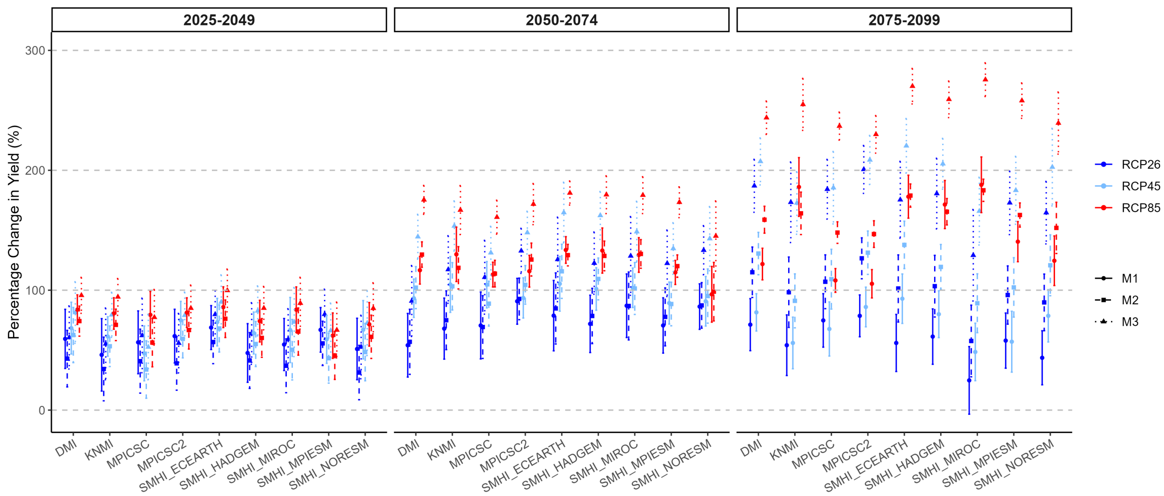


Notes: Predicted percentage changes in yield relative to the reference period (1999–2019) for nine climate simulations, time horizons (2025–2049, 2050–2074, 2075–2099) under three emissions scenarios (RCP2.6, RCP4.5, and RCP8.5) using M1. A point indicates the point estimate and whiskers show the 95% confidence interval.

The percentage change in yield varies to a large extent across emission scenarios, with differences between scenarios becoming more pronounced over time, particularly under the highest-emission pathway, RCP8.5. Interestingly, RCP8.5, representing the scenario with the most intense climate change, exhibits the highest yield increases, whereas RCP2.6, the scenario with the lowest emissions, results in substantially lower yield increases (and potential losses). This trend aligns with the observed reduction in frost days under RCP8.5, suggesting that the positive impact of fewer frost days outweighs the negative effects of increased heat stress in this scenario. It is clear that uncertainty in climate predictions increases as we look further into the future and as climate change intensifies. Predictions across climate scenarios are much more accurate for the 2025–2049 time horizon. The widest spread in predictions across climate scenarios is observed for RCP8.5 in the 2075–2099 time horizon.

Nevertheless, model uncertainty remains in these projections. To address this, we present additional yield projections based on the second-best (M3) and third-best (M2) performing models, as shown in Figure 13. The primary differences between the models lie in their estimation of winter chilling. Initially, the yield projections from the three models – M1, M2, and M3 – show relatively small differences, indicating minimal influence of the chill model selection on early estimates. However, as we look further into the future, to horizons 2050–2075 and 2075–2099, the divergence between models increases, highlighting the growing importance of chill model choice in accurately forecasting yield outcomes.

Figure 13: Percentage Changes in Yield – Across Models



Notes: Predicted percentage changes in yield relative to the reference period for models M1, M2, and M3. Point estimates for M1 are displayed with a dot, for M2 with a square, and for M3 with a triangle. Whiskers show the 95% confidence interval.

Additionally, we explored the variability in yield projections for individual orchards. Most orchards are anticipated to experience yield increases in the future, with only a small proportion expected to incur yield losses. Notably, the number of orchards with yield gains increases across time horizons and RCP scenarios. Interestingly, the horizon 2050–2074 under RCP2.6 exhibits the highest proportion of yield loss among orchards. This may be due to the shift in blooming dates aligning with spring frost occurrences, as the earlier start to the growing season has not yet been fully offset by a warmer climate. Further analysis is needed to confirm this hypothesis. Figure 19 in the Appendix presents the projected average percentage yield change for each orchard across various time horizons under the three RCPs for the DMI climate scenario.

1.6 Discussion and Conclusions

There is a large body of research on the impact of climate on agricultural yields in different disciplines and using different methods. The growing literature on panel models to assess these impacts has contributed significantly to the understanding of climate impacts. However, there remains a gap in the literature regarding impacts on perennial crops. Furthermore, the effects of frost in the context of climate change are not yet fully understood.

Our work contributes to this topic by using a unique longitudinal dataset of apple yields over the time horizon 1999–2019. We use this past climate data to assess past impacts using panel models and then select the most appropriate model for predicting future yield impacts. The effects of frost depend strongly on the developmental stage of the tree, the BBCH stage, which has been neglected in previous studies. We use the PhenoFlex model to predict the full flowering stage based solely on temperature. We trim two parameters of the Phenoflex model based on phenological observation data provided by Agrometeo. Using a model that predicts full bloom based on temperature introduces a dynamic component to our predictions. Rather than making fixed assumptions about the timing of full flowering, we can dynamically adjust flowering dates in response to future temperature variations, as both the shift in the growing season and the timing of full bloom are temperature-dependent. And if the climate changes, these dates will also change. In calibrating the model, we focus on what we consider the two most critical parameters: cooling demand and heat accumulation. However, this approach is a simplification, as the PhenoFlex model includes a total of 12 parameters that could be adjusted to optimize model accuracy. Additional validation and sensitivity analyses could be undertaken, and the model could be calibrated by parameterizing all 12 factors.

Using the date of full bloom as a reference date, we approximated the other phenological stages using the phenological observation data. By creating an average time span between the different developmental stages, we were able to fully define the development of the tree and, hence, estimate frost days across the whole phenological development of the tree. However, it is very likely that the length of each phenological stage will adapt in the future according to climatic changes. A potential improvement would be to dynamically model all the different BBCH stages, which could lead to more accurate predictions of plant development. We then use the defined BBCH stages to create phenology-specific frost variables. Depending on how far the bud or flower is developed, the plant is susceptible to frost to varying degrees. By introducing phenology-dependent frost days, we are able to better absorb the effects of frost, compared to earlier studies. The death of buds or flowers, however, is not binary. There is no clear temperature threshold above which there is no flower death and below which it is one hundred percent. In future research, we aim to incorporate this by introducing a range of freezing temperatures that result in varying degrees of flower mortality. In addition to the frost indicators, we create several climate variables, such as growing degree hours, growing degree days, various cold indicators, and precipitation measures. Since we are dealing with perennial crops, the yield of the current year depends on the yield of the previous year. We partially take this effect into account by creating a delayed frost variable. After years with severe frost effects, the yield of the following year is higher, as the tree saves resources that are stored and can be used the following year.

Alongside models based on biophysical relationships, we also relied on Random Forest (RF) for variable selection. Our out-of-sample predictions and model validation indicate that models grounded in climate-yield relationships consistently outperform those relying on RF-based variable selection. Our findings show that models including the full set of phenology-dependent frost measures outperformed those using simpler frost measures or reduced forms. This highlights the importance of detailed frost measures in the analysis of perennial fruit crops. The selected model estimates a significantly positive, non-linear relationship between yield and temperature. Precipitation effects are positive with a slightly negative quadratic term, though not statistically significant. In contrast, frost variables exhibit large, negative, and significant impact on yield, with the largest yield risk due to frost during full bloom. Additionally, heat days lead to a decrease in yield.

Based on the past climate-yield relationship modeled by our chosen model, we project future yield changes under various climate scenarios. These scenarios are driven by different GCMs and RCMs. We selected a range of climate models to account for the considerable variation often observed between scenarios, which could otherwise introduce substantial biases in yield estimates. Our analysis indicates a projected yield increase across the different time horizons (2025–2049, 2050–2074. 2075–2099), consistently observed over all nine climate simulations. Notably, RCP8.5, the high-emission scenario, leads to the highest yield gains. We conjecture that this is the result of the combined effects of fewer frost days and a warmer climate. At this stage, heat stress does not significantly offset this positive impact. Currently, our heat stress variable is a binary indicator capturing occurrences of temperatures exceeding 30°C; however, the relationship between heat stress and yield is likely more complex. Further analysis could improve accuracy by capturing increasing harm through temperature rise exceeding the threshold of 30 degrees C.

On average, the spread of predicted yields under different emission scenarios is increasing over time. A significant portion of the variability can be explained by differences in climate scenarios. Predictions for the upcoming time horizon are much more consistent across scenarios compared to the following two horizons. In particular, forecasts for the most extreme emission scenario, projected far into the future, show a considerable spread. Predictions that reach far into the future, especially for extreme emission scenarios, exceed the limits of predictability. Alongside variability in climate scenarios, there remains considerable model uncertainty, as already mentioned by Lobell and Field (2011). When projecting future yield using M1, M2, and M3, the projected percentage change in yield is similar for the initial time horizon, yet the divergence among models grows in later time periods. The model structure is thus critical in determining future yields. The three best-performing models differ mainly in their methods for estimating winter chilling, raising the question of which approach provides the most accurate estimation. Further research in this area is needed to enable more robust long-term estimations. Our study contributes to the existing literature by enabling a comparison of various chilling estimation methods across different climate scenarios.

There is potential for future research in other areas using this unique longitudinal dataset. For example, our orchard-level data observes different varieties over time. This data would allow us to utilize the varietal differences over time, which could potentially lead to insights into which varieties perform better in future scenarios and which do not.

In summary, this study takes an important step in quantifying climate impacts on perennial crops, using a unique orchard-level dataset and incorporating bloom stage predictions and phenology-specific frost indicators. By incorporating the PhenoFlex model and adjusting for phenology-specific frost risks, we provide a nuanced view of how climate variability interacts with crop development stages. Our analysis shows that climate yield models outperform commonly used methods, highlighting the value of detailed frost and phenology data in predicting yield impacts. However, there remains some uncertainty in accurately capturing extreme heat impacts, winter chilling requirements, and optimal model selection, as research on these factors for perennial crops is still emerging. These areas offer valuable opportunities for further refinement and exploration, especially as climate patterns become increasingly variable. Overall, this study lays a foundation for advancing the estimation of yield risk in perennial crop production, providing actionable insights on frost impact.

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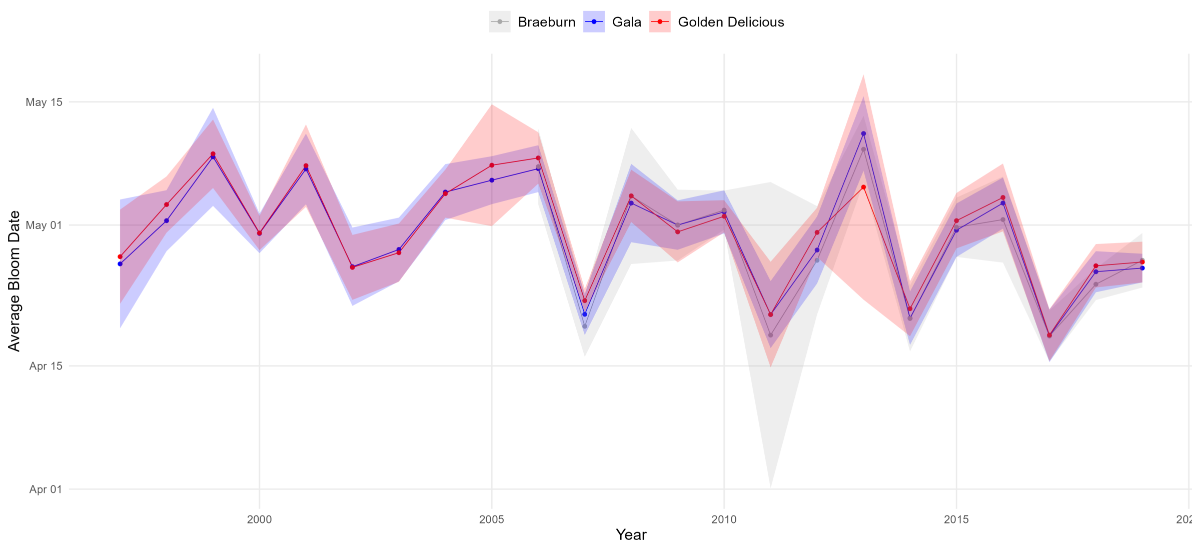
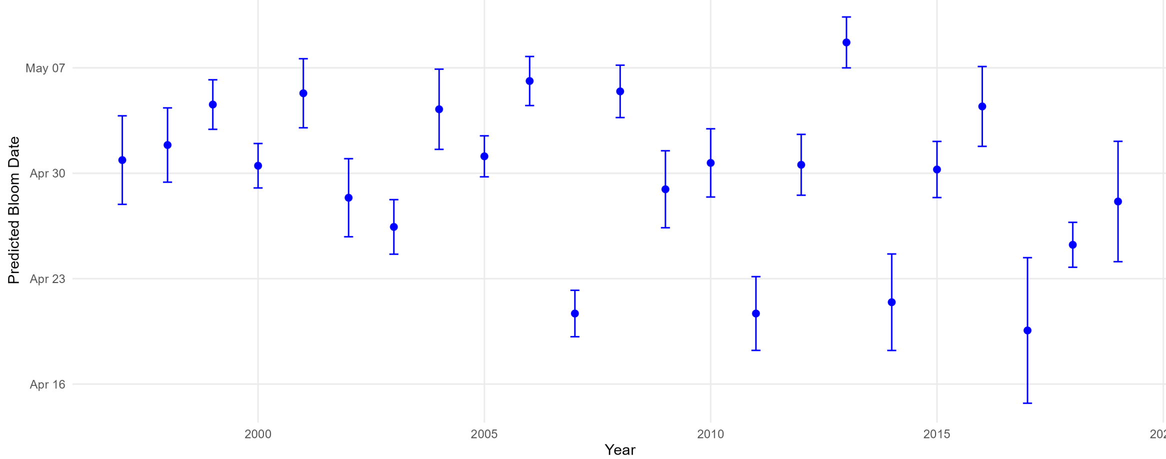
Appendix

Figure 14: Average Bloom Dates



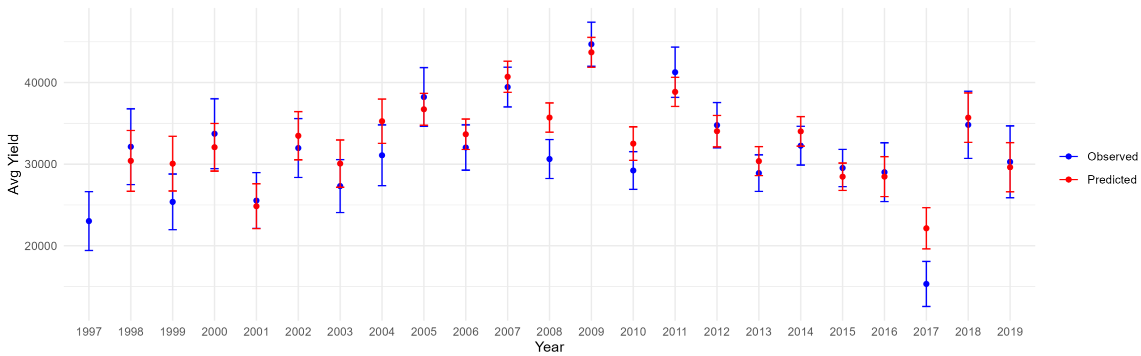
Notes: Bloom dates for the three apple varieties (Braeburn, Gala, and Golden Delicious) averaged across all stations. Data for Gala and Golden Delicious is available from 1997 to 2019, while data for Braeburn spans from 2006 to 2019.

Figure 15: Predicted Bloom Dates



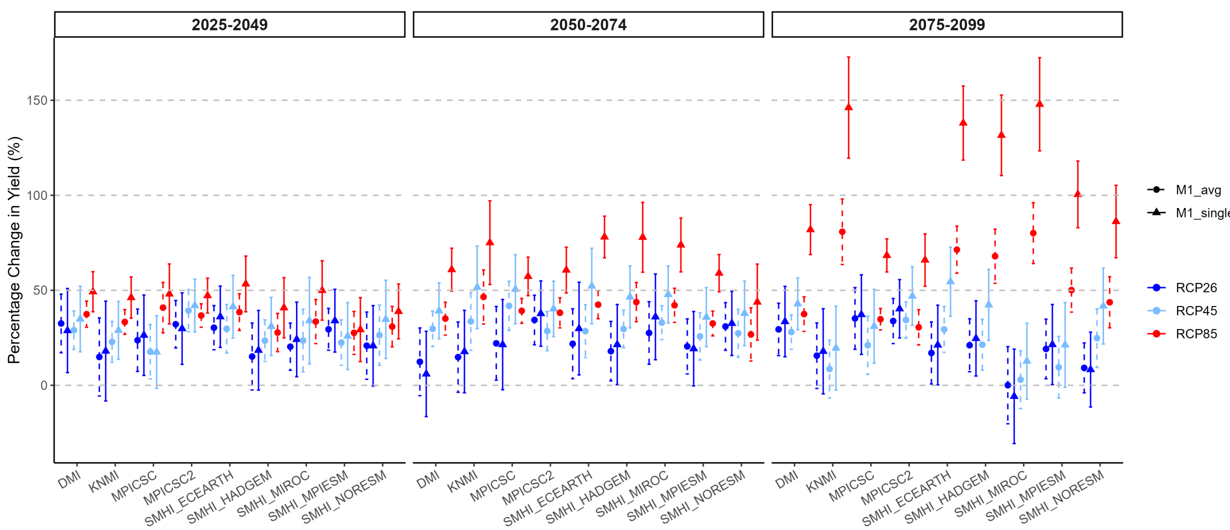
Notes: Predicted bloom date (BBCH65) over temperature measurement sites over the years 1997–2019 using PhenoFlex based on the calibrated parameters $y_c = 36$ and $z_c = 287$.

Figure 16: Predicted and Observed Yield (Year Split over all Years)



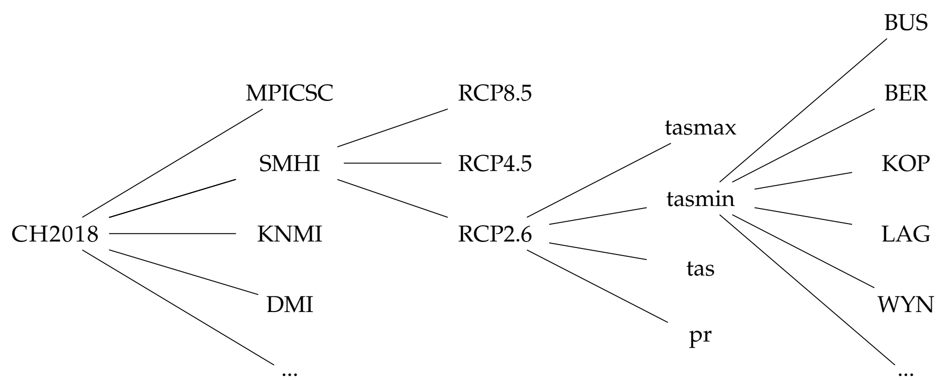
Notes: Predicted average yield and observed yield from out-of-sample predictions using M1. For each prediction, one year was excluded, the model was trained on the remaining years, and the yield for the excluded year was predicted.

Figure 17: Percentage Changes in Yield - Single and Averaged Varieties



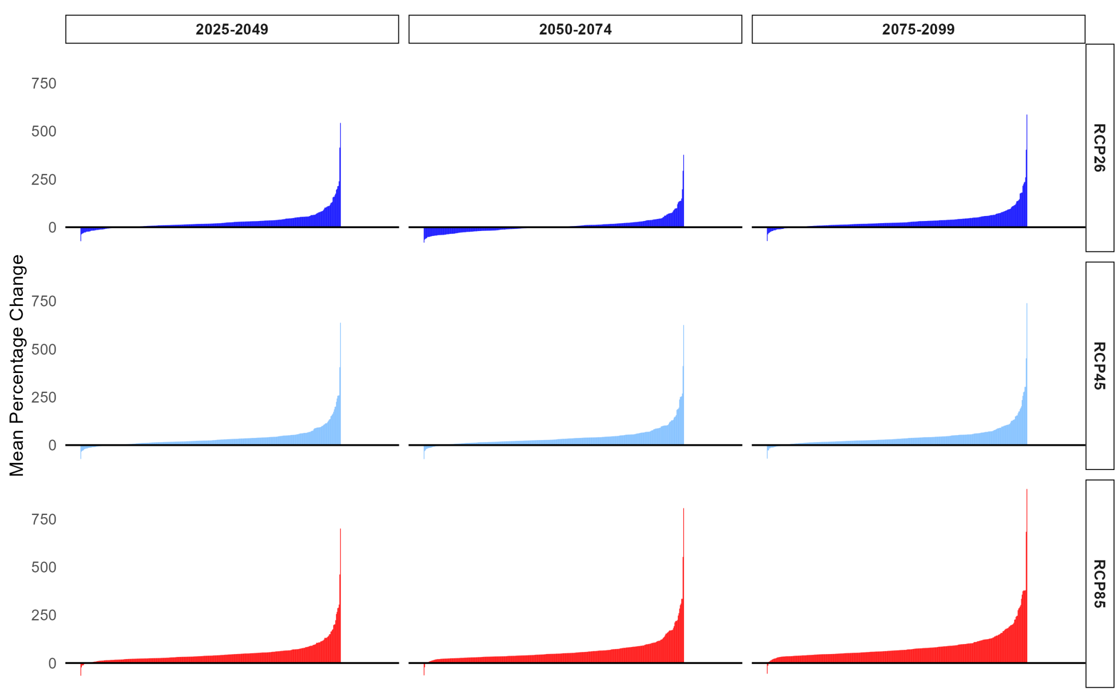
Notes: Projected percentage changes in crop yield relative to the baseline period (1999–2019) based on nine climate models, evaluated across three future time periods (2025–2049, 2050–2074, 2075–2099) under three emissions pathways (RCP2.6, RCP4.5, and RCP8.5). Points represent point estimates, with whiskers indicating the 95% confidence intervals. The "M1_single" model shows yield changes when orchards are restricted to single varieties, whereas "M1_avg" illustrates yield changes averaged across multiple varieties within each orchard.

Figure 18: CH2018 Data



Notes: Overview of the CH2018 climate scenario data availability. For each of the nine climate simulations, data are available for three Representative Concentration Pathways (RCPs), representing distinct emissions scenarios. For each RCP, data include four climate variables: maximum temperature, minimum temperature, mean temperature, and precipitation. These measurements are collected from various stations distributed across Switzerland.

Figure 19: Percentage Changes in Yield over Orchards



Notes: Predicted percentage changes in yield relative to the reference period for each individual orchard over the different RCPs and time horizons for the climate scenario DMI.

Table 5: What Do We Learn from the Weather? (Dell et al. 2014)

Paper	Outcome variable(s)	Weather variables	Weather measures	Time unit	Panel unit	Non-weather Regressors	Error structure
Emerick (2010)	Crop yields, crop revenues, adjustment measures	Temperature, Precipitation	Growing season, degree days and precipitation	Five year to twenty year, periods for the long differences (annual for panel)	County	No	Clustered by state
Deschenes and Greenstone (2007)	Agricultural profits	Temperature, Precipitation	Growing season, degree-days and total, precipitation	Year	County	No	Clustered at the county level; Conley (1999)
Feng et al. (2010)	Crop yields; migration	Temperature, Precipitation	Levels, levels squared	Five-year periods	State	No	Robust standard errors
Feng et al. (2012)	Crop yields; net outmigration	Temperature, Precipitation	Moderate and extreme degree days; precipitation and precipitation squared	Five-year periods	County	No	Clustered by state
Fishman (2011)	Log crop yield	Temperature, Precipitation	Growing season, degree day anomalies; precipitation anomalies; intraseasonal variation of rainfall anomalies; number of rainy days anomalies; (also in levels)	Year	District	Yes (lagged dependent variable, time varying irrigation measure)	Clustered by state
Hidalgo et al. (2010)	Agricultural income, land invasions	Precipitation	Absolute value of average monthly anomalies; squared anomalies	Year	Municipality	Yes (time varying controls)	Clustered by municipality
Guiteras (2007)	Crop yields	Temperature, Precipitation	Growing season moderate and extreme degree days and squares; monthly precipitation and squares; temperature bins	Year	District	No	Two-way clustering by district and state x year
Jayachandran (2006)	Agricultural yields; agricultural wage	Rainfall	Rain shock variable	Year	District	No	Clustered by region-year
Levine and Yang (2006)	Rice output	Rainfall	ln(rainfall)-ln(mean rainfall)	Year	District	No	Clustered by province
Lobell et al. (2011)	Crop yields	Temperature, Precipitation	Temperature and precipitation levels and squares (detrended and observed); max and min temperature	Year	Country	No	Bootstrap
Schlenker and Lobell (2010)	Crop yields	Temperature, Precipitation	Temperature and precipitation levels; levels and their squares; degree days and a quadratic in precipitation; degree day bins and a quadratic in precipitation	Year	Country	No	Bootstrap
Schlenker and Roberts (2009)	Crop yields	Temperature, Precipitation	Bins	Year	County	No	Conley (1999)
Welch et al. (2010)	Crop yields	Temperature, Radiation	Levels of min temperature during the vegetative, reproductive, and ripening phases; max temperature, radiation, and precipitation during the same phases	Season-year	Farm	Yes (time varying controls)	Cluster by village/district; bootstrapped
Yang and Choi (2007)	Domestic income	Dry and wet season rainfall	Levels	Year	Household	No	Clustered by weather station, coverage area

Table 6: Weather Stations and Their Coordinates

Code	Canton	Station	Latitude	Longitude	Dataset
AIG	VD	Aigle	46.31903	6.970566	Temp
BAS	BL	Basel / Binningen	47.53787	7.570988	Temp/CH2018
BUS	AG	Buchs / Aarau	47.39106	8.079827	Temp/CH2018
CGI	VD	Nyon / Changins	46.39893	6.232703	Temp/CH2018
EBK	SG	Ebnat-Kappel	47.26548	9.123547	Temp
GOE	SO	Gösgen	47.37294	7.992262	Temp
GUT	TG	Güttingen	47.60356	9.287589	Temp/Prec/CH2018
GVE	GE	Genève / Cointrin	46.20990	6.144073	Temp/Prec/CH2018
KOP	BE	Koppigen	47.13372	7.601787	Temp
LUZ	LU	Luzern	47.05017	8.309307	Temp/Prec/CH2018
NEU	NE	Neuchâtel	46.98999	6.929273	Temp/CH2018
PAY	VD	Payerne	46.82203	6.940566	Temp/Prec/CH2018
PUY	VD	Pully	46.50927	6.665495	Temp/CH2018
RAG	SG	Bad Ragaz	47.00341	9.501106	Temp/CH2018
TAE	TG	Aadorf / Tänikon	47.47957	8.907980	Temp
WAE	ZH	Wädenswil	47.22969	8.671819	Temp/CH2018
ABE	BE	Aarberg	47.04206	7.275101	Prec
AMW	TG	Amriswil	47.54497	9.300241	Prec
BEX	VD	Bex	46.24998	7.014266	Prec
BIE	VD	Bière	46.53738	6.333969	Prec
BIZ	TG	Bischofszell / Sitterdorf	47.50367	9.247592	Prec
CGI	VD	Nyon / Changins	46.39893	6.232703	Prec
CHU	GR	Chur	46.85078	9.531986	Prec
EGO	LU	Egolzwil	47.18471	8.007183	Prec
ESZ	TG	Eschenz	47.64815	8.873392	Prec
FLW	SG	Flawil	47.41337	9.187030	Prec
HEK	SO	Hessigkofen	47.14130	7.466060	Prec
KUE	ZH	Küsnacht, ZH	47.31892	8.584471	Prec
LSN	VD	Lausanne	46.51965	6.632273	Prec
MOE	AG	Möhlin	47.55913	7.844253	Prec
MUR	AG	Muri, AG	47.27358	8.341557	Prec
SAX	SG	Salez / Saxerriet	47.22666	9.481674	Prec
UBB	AG	Bözberg	47.49706	8.154698	Prec
BER	BE	Bern / Zollikofen	46.99826	7.451339	CH2018
HAI	TG	Salen-Reutenen	47.65029	9.015740	CH2018
SIO	VS	Sion	46.23312	7.360626	CH2018
STG	SG	St. Gallen	47.42448	9.376717	CH2018

Table 7: Percentage Changes in Climate Variables [1]

Model	RCP	Time Horizon	Metrics								
			Prec	Tmean	GDD	Frost	HDD	Chillhrs	Utah	Chillprt	GDH
DMI	RCP26	2025-2049	-30.7	0.3	0.7	-0.2	-18.7	0.3	38.3	4.5	-0.6
		2050-2074	-30.7	0.6	2.7	12.0	29.4	0.2	26.8	5.0	-1.4
		2075-2099	-29.3	3.6	5.3	-5.0	2.2	0.5	28.7	4.4	1.5
	RCP45	2025-2049	-29.8	4.0	6.9	-0.1	53.6	-1.8	7.4	0.4	3.8
		2050-2074	-27.6	6.8	9.2	-16.0	81.9	-2.0	11.3	1.9	5.3
		2075-2099	-23.0	8.6	11.2	-26.5	86.4	-4.0	4.3	0.2	7.1
	RCP85	2025-2049	-27.0	5.2	7.1	-14.2	62.3	-3.3	11.4	1.0	5.6
		2050-2074	-22.5	12.8	17.2	-27.7	124.4	-9.7	-28.1	-4.4	12.7
		2075-2099	-20.9	23.4	31.5	-56.4	276.3	-20.2	-86.5	-11.5	22.6
KNMI	RCP26	2025-2049	-28.6	4.0	6.5	-6.4	41.1	-8.0	6.9	-0.6	4.9
		2050-2074	-25.3	4.2	5.8	-16.5	-4.7	-10.4	3.8	-2.6	7.4
		2075-2099	-30.2	5.5	8.1	-14.4	30.6	-10.3	-4.4	-3.8	7.5
	RCP45	2025-2049	-33.6	7.4	10.0	-20.0	90.0	-7.7	-0.7	-2.5	6.1
		2050-2074	-32.6	13.6	18.2	-31.7	116.7	-16.1	-40.9	-8.1	15.8
		2075-2099	-23.4	12.4	16.8	-23.6	103.5	-21.1	-44.6	-8.3	16.5
	RCP85	2025-2049	-22.5	6.5	8.7	-24.2	36.2	-10.3	-6.9	-3.1	10.2
		2050-2074	-20.9	15.8	21.5	-40.7	103.1	-23.5	-76.5	-12.8	22.2
		2075-2099	-26.5	32.5	44.6	-59.5	369.7	-38.9	-176.0	-24.9	33.8
MPICSC	RCP26	2025-2049	-25.8	2.2	2.5	-19.1	11.7	0.2	47.6	5.2	1.0
		2050-2074	-26.4	0.6	0.8	-13.1	20.5	-0.9	50.6	6.0	-0.1
		2075-2099	-29.0	1.9	1.5	-23.1	23.8	2.2	60.0	7.9	-1.8
	RCP45	2025-2049	-26.1	1.6	2.9	-7.3	57.0	2.6	45.1	6.4	-1.4
		2050-2074	-18.2	2.2	2.2	-18.3	29.5	0.0	52.9	7.9	-0.3
		2075-2099	-27.7	7.4	10.1	-25.2	99.8	-5.0	14.4	2.8	5.0
	RCP85	2025-2049	-24.1	1.6	1.6	-13.8	10.5	-1.4	48.1	6.1	1.5
		2050-2074	-21.5	7.9	9.4	-36.3	70.1	-6.4	21.0	2.8	8.2
		2075-2099	-26.1	18.1	23.0	-59.2	187.0	-18.7	-30.3	-4.4	17.9
MPICSC2	RCP26	2025-2049	-23.6	-0.7	0.2	8.3	-2.7	3.7	49.1	6.4	-1.6
		2050-2074	-28.6	2.5	3.3	-5.7	26.8	1.5	38.1	4.9	0.5
		2075-2099	-32.1	4.3	5.8	-7.8	31.3	0.0	22.1	2.1	2.8
	RCP45	2025-2049	-29.7	1.5	3.0	7.5	18.6	0.9	33.0	3.2	1.9
		2050-2074	-30.2	7.3	10.0	-10.6	71.5	-0.8	16.2	1.4	7.0
		2075-2099	-26.3	7.8	10.2	-24.3	42.2	-5.9	6.3	0.2	8.9
	RCP85	2025-2049	-23.5	4.2	6.2	-1.4	50.2	-1.1	16.4	3.0	3.7
		2050-2074	-28.8	12.6	16.8	-27.3	120.5	-9.8	-28.2	-4.8	14.5
		2075-2099	-20.4	18.5	24.6	-48.3	186.6	-18.1	-49.1	-5.6	18.6
SMHI ECEARTH	RCP26	2025-2049	-25.7	4.0	5.6	-16.8	6.5	-3.7	24.2	1.9	4.0
		2050-2074	-25.1	4.5	6.2	-21.4	-9.2	-5.8	20.5	0.4	5.2
		2075-2099	-23.1	4.6	5.6	-21.2	-31.6	-3.7	22.3	0.9	5.3
	RCP45	2025-2049	-29.8	6.4	8.9	-17.5	55.7	-3.5	8.1	-0.2	5.5
		2050-2074	-30.2	13.1	17.0	-37.3	100.3	-9.9	-14.3	-3.2	12.0
		2075-2099	-27.3	14.7	18.6	-47.2	123.6	-13.6	-23.6	-4.1	13.7
	RCP85	2025-2049	-26.7	7.2	8.8	-25.2	29.5	-5.5	8.0	-0.8	9.7
		2050-2074	-31.2	20.1	27.1	-44.9	203.6	-19.1	-69.7	-9.9	19.3
		2075-2099	-31.8	32.7	43.9	-67.4	370.3	-29.8	-140.8	-19.6	29.5

Table 8: Percentage Changes in Climate Variables [2]

Model	RCP	Time Horizon	Metrics								
			Prec	Tmean	GDD	Frost	HDD	Chillhrs	Utah	Chillprt	GDH
SMHI HADGEM	RCP26	2025-2049	-29.5	3.8	6.7	-7.1	95.6	-5.6	5.4	-1.2	3.0
		2050-2074	-19.0	2.9	4.7	-10.9	48.0	-9.2	14.1	-0.3	3.7
		2075-2099	-22.0	3.5	5.7	-12.5	79.4	-8.8	8.9	-1.9	4.5
	RCP45	2025-2049	-22.5	4.8	6.8	-21.8	87.7	-6.1	17.2	-0.7	3.4
		2050-2074	-26.7	10.9	14.2	-37.8	121.9	-12.4	-10.5	-5.0	11.2
		2075-2099	-18.6	13.2	18.2	-33.5	189.8	-17.0	-33.8	-6.9	12.5
	RCP85	2025-2049	-14.4	6.8	9.6	-25.0	82.0	-9.5	-4.4	-2.5	8.2
		2050-2074	-15.9	15.8	21.6	-43.2	202.2	-18.3	-64.7	-11.5	16.8
		2075-2099	-20.2	30.3	41.4	-65.4	424.9	-33.7	-151.6	-22.8	28.1
SMHI MIROC	RCP26	2025-2049	-22.5	5.4	7.8	-15.3	36.4	-2.4	19.5	1.9	3.5
		2050-2074	-18.4	5.1	6.8	-13.2	-3.0	-4.7	21.4	0.9	6.6
		2075-2099	-20.0	1.2	2.5	-0.6	8.0	-3.8	33.4	2.8	2.3
	RCP45	2025-2049	-20.0	5.7	6.9	-24.8	32.5	-1.7	29.3	3.4	3.1
		2050-2074	-22.8	8.6	10.8	-29.8	55.0	-8.3	10.2	0.0	8.9
		2075-2099	-14.8	9.5	12.9	-25.1	74.7	-8.8	-2.7	-1.7	10.5
	RCP85	2025-2049	-18.5	8.3	10.5	-34.6	11.4	-9.1	1.1	-1.5	11.2
		2050-2074	-16.9	14.8	19.3	-42.7	75.5	-17.3	-37.5	-6.7	18.9
		2075-2099	-26.1	30.9	41.2	-75.1	251.2	-33.8	-133.8	-20.9	32.8
SMHI MPIESM	RCP26	2025-2049	-27.8	4.8	5.8	-20.0	40.2	-2.1	28.3	2.2	3.9
		2050-2074	-30.9	4.4	5.8	-16.1	59.4	-3.1	28.0	2.6	3.1
		2075-2099	-28.5	5.3	6.1	-25.3	51.7	-0.3	36.0	4.5	1.4
	RCP45	2025-2049	-28.9	5.5	7.7	-15.2	83.7	0.6	30.3	3.7	1.5
		2050-2074	-22.8	6.3	7.8	-22.8	97.7	-3.5	30.6	4.2	2.9
		2075-2099	-28.7	10.7	14.3	-29.6	148.0	-7.7	-2.1	-0.7	7.8
	RCP85	2025-2049	-22.7	2.9	3.8	-14.0	29.1	-3.4	31.4	3.3	4.2
		2050-2074	-24.3	14.1	17.7	-46.0	177.0	-12.6	-14.5	-3.1	12.0
		2075-2099	-32.7	27.1	35.6	-67.9	326.5	-26.4	-84.9	-13.0	22.6
SMHI NORESM	RCP26	2025-2049	-27.4	2.1	3.3	-8.2	34.9	-1.3	43.9	6.0	-0.4
		2050-2074	-27.9	3.2	3.7	-13.0	12.5	-2.9	45.0	4.6	2.0
		2075-2099	-30.9	4.2	5.4	-16.7	0.7	-5.0	22.2	1.0	3.9
	RCP45	2025-2049	-30.3	5.6	7.4	-14.6	53.9	-3.5	24.9	2.9	3.3
		2050-2074	-31.0	8.5	11.2	-26.0	82.4	-8.4	11.8	1.1	7.3
		2075-2099	-28.9	11.2	14.0	-38.5	61.6	-10.3	3.2	-1.6	11.6
	RCP85	2025-2049	-32.3	6.1	7.8	-16.6	31.3	-5.4	15.4	1.0	6.8
		2050-2074	-29.2	12.3	17.2	-22.3	100.6	-14.9	-32.2	-5.2	14.0
		2075-2099	-28.5	23.0	30.8	-50.5	241.9	-24.2	-81.7	-12.4	21.9

Notes: Percentage changes in climate variables across scenarios, RCPs, and time horizons (2025–2049, 2050–2074, 2075–2099) relative to the baseline period (1999–2019). The table presents percentage changes for multiple variables: precipitation (Prec), mean temperature (Tmean), growing degree days (GDD), frost days (FrostD), heat degree days (HDD), chilling hours (Chillhrs), Utah model chilling units (Utah), chill portions (Chillprt), and growing degree hours (GDH). Data are aggregated across nine climate simulations, grouped by scenario, RCP, and time horizon.

Table 9: Absolute Change of Frost Variables by Scenario, RCP, and Time Horizon [1]

Model	RCP	Time Horizon	Frost51	Frost53	Frost54	Frost56	Frost57	Frost59	Frost61	Frost65	Frost69
DMI	RCP26	2025-2049	0.1	0.8	0.6	0.6	0.3	0.1	0.0	0.0	0.0
		2050-2074	0.2	1.2	1.1	0.8	0.4	0.3	0.1	0.0	0.1
		2075-2099	0.2	0.3	0.3	0.9	0.6	0.5	0.1	0.0	0.1
	RCP45	2025-2049	0.2	0.7	0.3	0.8	0.1	0.1	0.1	0.0	0.0
		2050-2074	0.1	0.3	0.2	0.7	0.4	0.2	0.0	0.0	0.0
		2075-2099	0.0	0.4	0.3	0.3	0.3	0.0	0.1	0.0	0.0
	RCP85	2025-2049	0.1	0.2	0.2	0.2	0.0	0.0	0.0	0.0	0.0
		2050-2074	0.0	0.2	0.1	0.1	0.0	-0.1	0.0	0.0	0.0
		2075-2099	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0
KNMI	RCP26	2025-2049	0.3	0.6	0.6	0.5	0.7	0.5	0.4	0.1	0.2
		2050-2074	0.1	0.5	0.9	1.3	0.7	0.5	0.2	0.0	0.3
		2075-2099	0.1	0.5	0.9	1.2	1.0	0.4	0.6	0.0	0.2
	RCP45	2025-2049	0.1	0.5	0.4	0.3	0.3	0.2	0.1	0.0	0.2
		2050-2074	0.0	0.3	0.4	0.7	0.7	0.4	0.2	0.0	0.0
		2075-2099	0.1	0.4	0.9	0.7	1.0	0.8	0.4	0.0	0.3
	RCP85	2025-2049	0.1	0.2	0.4	0.6	0.2	0.1	0.1	0.0	0.0
		2050-2074	0.0	0.3	0.4	0.5	0.4	0.2	0.2	0.0	0.0
		2075-2099	0.0	0.0	0.1	0.4	0.8	0.0	0.0	0.0	0.0
MPICSC	RCP26	2025-2049	0.1	0.8	1.0	0.4	0.2	0.2	0.0	0.0	0.0
		2050-2074	0.2	1.1	0.7	0.5	0.1	0.2	0.0	0.0	0.1
		2075-2099	0.4	0.5	0.3	0.2	0.2	0.6	0.3	0.0	0.1
	RCP45	2025-2049	0.3	0.8	1.2	0.8	0.2	0.0	0.1	0.0	0.0
		2050-2074	0.2	0.4	0.3	0.2	0.2	0.2	0.2	0.0	0.1
		2075-2099	0.3	0.5	0.6	0.2	0.4	0.4	0.3	0.0	0.0
	RCP85	2025-2049	0.2	0.6	0.4	0.4	0.0	0.0	0.0	0.0	0.0
		2050-2074	0.0	0.2	0.2	0.3	0.0	0.0	0.0	0.0	0.0
		2075-2099	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0
MPICSC2	RCP26	2025-2049	0.1	0.5	0.6	1.0	0.8	0.1	0.0	0.0	0.0
		2050-2074	0.1	0.3	0.6	0.5	0.4	0.2	0.1	0.0	0.1
		2075-2099	0.3	0.2	0.3	0.6	0.4	0.3	0.3	0.0	0.2
	RCP45	2025-2049	0.1	0.3	0.4	0.3	0.1	0.1	0.1	0.0	0.1
		2050-2074	0.1	0.3	0.3	0.6	0.2	0.2	0.2	0.0	0.0
		2075-2099	0.1	0.2	0.3	0.1	0.6	0.1	0.1	0.0	0.0
	RCP85	2025-2049	0.2	0.4	0.1	0.2	0.2	0.0	0.0	0.0	0.0
		2050-2074	0.0	0.3	0.1	0.2	0.2	0.0	0.0	0.0	0.0
		2075-2099	0.0	0.3	0.1	0.1	0.0	0.0	0.0	0.0	0.0
SMHI ECEARTH	RCP26	2025-2049	0.4	0.4	0.2	0.5	0.4	0.3	0.1	0.0	0.0
		2050-2074	0.2	0.9	1.3	0.7	0.3	0.0	0.1	0.0	0.0
		2075-2099	0.0	0.4	0.4	1.2	1.2	0.7	0.6	0.0	0.1
	RCP45	2025-2049	0.2	0.4	0.4	0.2	0.2	0.1	0.2	0.0	0.0
		2050-2074	0.1	0.0	0.2	0.3	0.4	0.5	0.5	0.0	0.0
		2075-2099	0.0	0.3	0.4	0.2	0.3	0.1	0.2	0.0	0.0
	RCP85	2025-2049	0.1	0.3	0.1	0.1	0.2	0.1	0.0	0.0	0.0
		2050-2074	0.0	0.3	0.1	0.1	0.2	0.0	0.0	0.0	0.0
		2075-2099	0.0	0.1	0.1	0.0	0.0	-0.1	0.0	0.0	0.0

Table 10: Absolute Change of Frost Variables by Scenario, RCP, and Time Horizon [2]

Model	**RCP**	**Time Horizon**	Frost51	Frost53	Frost54	Frost56	Frost57	Frost59	Frost61	Frost65	Frost69
SMHI HADGEM	RCP26	2025-2049	0.6	0.5	0.6	0.4	0.2	0.5	0.8	0.1	0.1
		2050-2074	0.0	0.4	0.9	0.6	0.5	0.6	0.6	0.0	0.1
		2075-2099	0.2	0.5	0.6	1.1	0.8	0.3	0.3	0.0	0.0
	RCP45	2025-2049	0.1	0.1	0.3	0.5	0.5	0.2	0.1	0.0	0.1
		2050-2074	0.0	0.3	0.3	0.2	0.3	0.2	0.2	0.0	0.0
		2075-2099	0.0	0.3	0.2	0.6	0.7	0.3	0.3	0.0	0.1
	RCP85	2025-2049	0.1	0.5	0.2	0.4	0.4	0.0	0.0	0.0	0.0
		2050-2074	0.2	0.2	0.1	0.2	0.0	-0.1	0.1	0.0	0.0
		2075-2099	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0
SMHI MIROC	RCP26	2025-2049	0.2	0.3	0.6	0.8	1.2	0.4	0.2	0.0	0.1
		2050-2074	0.0	0.4	0.6	0.9	0.9	0.4	0.3	0.0	0.1
		2075-2099	0.1	0.5	0.5	1.4	2.0	1.6	0.9	0.0	0.6
	RCP45	2025-2049	0.0	0.2	0.4	0.3	0.8	0.6	0.4	0.0	0.0
		2050-2074	0.0	0.2	0.4	0.8	0.5	0.1	0.3	0.0	0.2
		2075-2099	0.0	0.3	0.5	0.7	1.0	0.8	0.2	0.0	0.6
	RCP85	2025-2049	0.1	0.3	0.3	0.6	0.5	0.0	0.1	0.0	0.2
		2050-2074	0.0	0.2	0.2	0.2	0.1	0.0	0.0	0.0	0.0
		2075-2099	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0
SMHI MPIESM	RCP26	2025-2049	0.0	0.6	0.3	0.2	0.3	0.1	0.1	0.0	0.0
		2050-2074	0.2	0.7	0.3	0.5	0.9	0.1	0.1	0.0	0.1
		2075-2099	0.0	0.6	0.4	0.8	0.5	0.7	0.2	0.0	0.2
	RCP45	2025-2049	0.3	0.8	0.5	1.1	0.3	0.0	0.1	0.0	0.0
		2050-2074	0.1	0.3	0.2	0.7	0.2	0.3	0.1	0.0	0.2
		2075-2099	0.1	0.5	0.7	0.7	0.4	0.6	0.6	0.0	0.1
	RCP85	2025-2049	0.3	0.6	0.7	0.4	0.3	0.0	0.0	0.0	0.0
		2050-2074	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0
		2075-2099	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0
SMHI NORESM	RCP26	2025-2049	0.4	0.7	1.0	0.7	0.3	0.2	0.3	0.0	0.1
		2050-2074	0.1	0.3	0.5	0.6	0.6	0.4	0.3	0.0	0.1
		2075-2099	0.3	0.5	0.9	0.9	0.9	0.7	0.3	0.0	0.3
	RCP45	2025-2049	0.2	0.4	0.4	1.0	0.6	0.5	0.3	0.0	0.2
		2050-2074	0.2	0.3	0.5	0.5	0.9	0.1	0.4	0.0	0.1
		2075-2099	0.0	0.3	0.4	0.4	0.5	0.6	0.1	0.0	0.1
	RCP85	2025-2049	0.2	0.3	0.4	0.6	0.5	0.3	0.1	0.0	0.0
		2050-2074	0.1	0.5	0.7	0.3	0.6	0.1	0.1	0.0	0.1
		2075-2099	0.0	0.1	0.1	0.5	0.2	0.1	0.2	0.1	0.0

Notes: Absolute changes in phenology-dependent frost variables across scenarios, RCPs, and time horizons (2025–2049, 2050–2074, 2075–2099), compared to the baseline period (1999–2019). The table presents absolute changes for specific frost days across phenological stages, labeled as Frost51, Frost53, Frost54, Frost56, Frost57, Frost59, Frost61, Frost65, and Frost69, where Frost51 is a frost event based on the critical temperatures defined in Table 2 in BBCH stage 51. Data are averaged across nine climate simulations and organized by scenario, RCP, and time horizon.

Table 11: Descriptive Statistics for Climate Variables Across RCPs and Time Horizons [1]

RCPs	Horizon	Prec	Tmean	GGD	Frost	HDG	BB51	BB53	BB54	BB56	BB57	BB59	BB61	BB65	BB69	Chillhrs	Utah	Chillprt	GDH
DMI																			
RCP26	2025-2049	705	3170	2110	31	8	0	1	1	1	0	0	0	0	0	2439	1322	150	58037
RCP26	2050-2074	705	3179	2151	35	13	0	1	1	1	0	0	0	0	0	2435	1213	150	57554
RCP26	2075-2099	719	3275	2207	30	10	0	0	0	1	1	1	0	0	0	2442	1231	150	59280
RCP45	2025-2049	715	3288	2240	31	15	0	1	0	1	0	0	0	0	0	2387	1028	144	60601
RCP45	2050-2074	737	3375	2287	26	18	0	0	0	1	0	0	0	0	0	2382	1065	146	61475
RCP45	2075-2099	784	3434	2328	23	19	0	0	0	0	0	0	0	0	0	2333	998	143	62557
RCP85	2025-2049	743	3327	2244	27	16	0	0	0	0	0	0	0	0	0	2350	1066	145	61655
RCP85	2050-2074	789	3566	2454	23	22	0	0	0	0	0	0	0	0	0	2194	688	137	65828
RCP85	2075-2099	806	3902	2755	14	38	0	0	0	0	0	0	0	0	0	1940	129	127	71600
KNMI																			
RCP26	2025-2049	713	3248	2196	30	13	0	1	1	1	1	1	0	0	0	2256	1105	145	60497
RCP26	2050-2074	745	3252	2181	27	9	0	0	1	1	1	1	0	0	0	2190	1076	142	61872
RCP26	2075-2099	696	3294	2230	27	12	0	1	1	1	1	0	1	0	0	2184	995	140	62120
RCP45	2025-2049	661	3354	2270	25	17	0	0	0	0	0	0	0	0	0	2250	1015	142	61524
RCP45	2050-2074	672	3552	2443	22	20	0	0	0	1	1	0	0	0	0	2059	640	134	67062
RCP45	2075-2099	765	3513	2413	24	18	0	0	1	1	1	1	0	0	0	1938	621	134	67330
RCP85	2025-2049	772	3325	2242	24	12	0	0	0	1	0	0	0	0	0	2177	954	141	63818
RCP85	2050-2074	790	3623	2512	19	18	0	0	0	1	0	0	0	0	0	1870	306	127	70792
RCP85	2075-2099	733	4154	3005	13	44	0	0	0	1	1	0	0	0	0	1511	-661	110	77911
MPICSC																			
RCP26	2025-2049	742	3192	2113	26	10	0	1	1	0	0	0	0	0	0	2459	1501	154	58138
RCP26	2050-2074	741	3139	2076	28	11	0	1	1	1	0	0	0	0	0	2429	1533	155	57396
RCP26	2075-2099	711	3180	2091	25	11	0	1	0	0	0	1	0	0	0	2499	1618	157	56605
RCP45	2025-2049	739	3172	2121	29	14	0	1	1	1	0	0	0	0	0	2504	1457	155	56952
RCP45	2050-2074	821	3190	2107	26	12	0	0	0	0	0	0	0	0	0	2451	1544	157	57403
RCP45	2075-2099	724	3358	2274	24	18	0	1	1	0	0	0	0	0	0	2332	1177	150	60608
RCP85	2025-2049	763	3170	2094	27	10	0	1	0	0	0	0	0	0	0	2404	1492	155	58584
RCP85	2050-2074	787	3371	2257	20	15	0	0	0	0	0	0	0	0	0	2301	1248	150	62455
RCP85	2075-2099	745	3697	2544	13	26	0	0	0	0	0	0	0	0	0	2022	751	139	68150

Table 12: Descriptive Statistics for Climate Variables Across RCPs and Time Horizons [2]

RCPs	Horizon	Prec	Tmean	GGD	Frost	HDG	BB51	BB53	BB54	BB56	BB57	BB59	BB61	BB65	BB69	Chillhrs	Utah	Chillprt	GDH
MPICSC2																			
RCP26	2025-2049	760	3096	2064	34	9	0	1	1	1	1	0	0	0	0	2528	1492	155	56698
RCP26	2050-2074	712	3200	2130	30	11	0	0	1	1	0	0	0	0	0	2485	1396	152	57840
RCP26	2075-2099	679	3254	2181	30	12	0	0	0	1	0	0	0	0	0	2440	1244	149	59343
RCP45	2025-2049	706	3167	2123	34	11	0	0	0	0	0	0	0	0	0	2460	1339	150	58829
RCP45	2050-2074	697	3349	2271	28	16	0	0	0	1	0	0	0	0	0	2433	1181	147	61748
RCP45	2075-2099	739	3364	2273	24	13	0	0	0	0	1	0	0	0	0	2311	1101	146	62695
RCP85	2025-2049	763	3253	2191	31	14	0	0	0	0	0	0	0	0	0	2406	1169	149	60023
RCP85	2050-2074	709	3520	2413	23	20	0	0	0	0	0	0	0	0	0	2212	762	139	66195
RCP85	2075-2099	801	3707	2577	16	27	0	0	0	0	0	0	0	0	0	2036	564	137	68624
SMHI ECEARTH																			
RCP26	2025-2049	745	3246	2176	27	9	0	1	0	1	1	0	0	0	0	2356	1270	148	59917
RCP26	2050-2074	752	3261	2188	25	8	0	1	2	1	0	0	0	0	0	2305	1241	146	60546
RCP26	2075-2099	769	3265	2176	25	6	0	0	0	1	1	1	1	0	0	2344	1255	147	60684
RCP45	2025-2049	702	3322	2245	26	14	0	0	0	0	0	0	0	0	0	2348	1105	145	61002
RCP45	2050-2074	699	3536	2414	20	18	0	0	0	0	0	1	1	0	0	2211	895	141	64777
RCP45	2075-2099	727	3587	2448	17	20	0	0	0	0	0	0	0	0	0	2125	817	140	65707
RCP85	2025-2049	736	3347	2242	24	12	0	0	0	0	0	0	0	0	0	2304	1110	144	63453
RCP85	2050-2074	691	3757	2628	18	28	0	0	0	0	0	0	0	0	0	1978	373	131	69150
RCP85	2075-2099	685	4156	2986	10	44	0	0	0	0	0	0	0	0	0	1742	-316	117	75372
SMHI HADGEM																			
RCP26	2025-2049	700	3239	2200	30	18	1	0	1	0	0	1	1	0	0	2311	1083	144	59439
RCP26	2050-2074	807	3211	2158	28	13	0	0	1	1	1	1	1	0	0	2222	1168	145	59808
RCP26	2075-2099	774	3231	2179	28	16	0	1	1	1	1	0	0	0	0	2222	1119	143	60366
RCP45	2025-2049	767	3271	2202	25	17	0	0	0	1	1	0	0	0	0	2290	1191	145	59789
RCP45	2050-2074	726	3465	2356	20	20	0	0	0	0	0	0	0	0	0	2159	942	139	64218
RCP45	2075-2099	811	3539	2442	21	27	0	0	0	1	1	0	0	0	0	2038	720	136	65020
RCP85	2025-2049	848	3335	2260	24	17	0	0	0	0	0	0	0	0	0	2201	978	142	62641
RCP85	2050-2074	837	3622	2514	18	28	0	0	0	0	0	0	0	0	0	1992	421	129	67624
RCP85	2075-2099	792	4083	2938	11	50	0	0	0	0	0	0	0	0	0	1640	-420	113	74424

Table 13: Descriptive Statistics for Climate Variables Across RCPs and Time Horizons [3]

RCPs	Horizon	Prec	Tmean	GGD	Frost	HDG	BB51	BB53	BB54	BB56	BB57	BB59	BB61	BB65	BB69	Chillhrs	Utah	Chillprt	GDH
SMHI MIROC																			
RCP26	2025-2049	767	3290	2222	27	12	0	0	1	1	1	0	0	0	0	2383	1221	148	59621
RCP26	2050-2074	812	3281	2202	28	9	0	0	1	1	1	0	0	0	0	2331	1242	147	61388
RCP26	2075-2099	796	3155	2111	32	10	0	1	1	2	2	2	1	0	1	2334	1354	150	59042
RCP45	2025-2049	800	3300	2203	24	12	0	0	0	0	1	1	0	0	0	2385	1308	150	59551
RCP45	2050-2074	767	3391	2286	22	14	0	0	0	1	1	0	0	0	0	2246	1134	146	62866
RCP45	2075-2099	847	3420	2329	24	16	0	0	1	1	1	1	0	0	1	2228	1017	143	63722
RCP85	2025-2049	813	3382	2277	21	10	0	0	0	1	1	0	0	0	0	2213	1038	143	64259
RCP85	2050-2074	827	3586	2463	18	16	0	0	0	0	0	0	0	0	0	2018	685	136	68758
RCP85	2075-2099	735	4100	2926	8	32	0	0	0	0	0	0	0	0	0	1633	-246	115	77059
SMHI MPIESM																			
RCP26	2025-2049	716	3269	2180	25	13	0	1	0	0	0	0	0	0	0	2395	1305	149	59888
RCP26	2050-2074	685	3258	2181	27	15	0	1	0	1	1	0	0	0	0	2374	1306	149	59440
RCP26	2075-2099	711	3287	2187	24	14	0	1	0	1	1	1	0	0	0	2428	1381	152	58555
RCP45	2025-2049	703	3291	2222	27	17	0	1	1	1	0	0	0	0	0	2452	1310	151	58693
RCP45	2050-2074	766	3317	2223	25	18	0	0	0	1	0	0	0	0	0	2365	1326	152	59358
RCP45	2075-2099	705	3457	2360	22	23	0	0	1	1	0	1	1	0	0	2264	1018	145	62272
RCP85	2025-2049	770	3210	2139	27	12	0	1	1	1	0	0	0	0	0	2355	1329	150	60194
RCP85	2050-2074	753	3567	2430	17	25	0	0	0	0	0	0	0	0	0	2149	909	142	64719
RCP85	2075-2099	667	3978	2809	10	40	0	0	0	0	0	0	0	0	0	1825	224	127	71059
SMHI NORESM																			
RCP26	2025-2049	721	3184	2129	29	12	0	1	1	1	0	0	0	0	0	2407	1447	154	57414
RCP26	2050-2074	718	3221	2136	28	10	0	0	1	1	1	0	0	0	0	2379	1471	152	58707
RCP26	2075-2099	689	3251	2171	27	9	0	1	1	1	1	1	0	0	0	2317	1253	147	59887
RCP45	2025-2049	693	3297	2214	27	14	0	0	0	1	1	1	0	0	0	2345	1266	150	59695
RCP45	2050-2074	685	3387	2294	24	17	0	0	1	1	1	0	0	0	0	2252	1152	147	61948
RCP45	2075-2099	706	3473	2351	20	15	0	0	0	0	1	1	0	0	0	2207	1078	144	64317
RCP85	2025-2049	672	3311	2222	27	12	0	0	0	1	1	0	0	0	0	2306	1177	147	61703
RCP85	2050-2074	703	3509	2420	25	18	0	1	1	0	1	0	0	0	0	2080	724	138	65909
RCP85	2075-2099	709	3848	2706	16	32	0	0	0	1	0	0	0	0	0	1875	250	128	70641

Chapter 2

To Adapt or Not to Adapt: How Swiss Fruit Farmers Respond to Climate Change

Abstract

Climate change presents a significant threat to global agricultural livelihoods, with the perennial crop sector facing unique challenges due to its inherent path dependencies. Using survey data from the year 2022, this paper examines the effects of severe droughts and spring frost over the past decade, adaptation strategies, climate perceptions, and beliefs of perennial crop farmers in Switzerland. Key findings include significant harvest losses, particularly from frost; however, there is a greater concern about future drought impacts. Farmers' estimates of temperature trends align more closely with projected trends than their assumptions about frost and precipitation, with those using fixed irrigation systems notably more accurate in recognizing precipitation trends than those without irrigation. Most farmers express concern about climate change and acknowledge the rise in global average temperatures. Climate skeptics demonstrate lower support for climate mitigation policies compared to believers but show a greater willingness to adapt. The study underscores the complexity of agricultural adaptation and the need for tailored solutions to enhance resilience against climatic changes.

Keywords: farmers' perception, farm adaptation, climate change, perennials

JEL-codes: Q12, Q15, Q54

2.1 Introduction

In agricultural landscapes, the effects of anthropogenic climate change are manifested not only through extreme weather events but also through more gradual changes such as shifts in temperature regimes, altered precipitation patterns, and prolonged or altered growing seasons, all of which pose significant challenges to farmers. Documented consequences in Switzerland highlight the significant effects of warming (MeteoSchweiz 2018) and projected alterations in the frequency and intensity of extreme weather events increase agriculture's vulnerability (CH2018 2018). Past severe heat waves and droughts in Europe underscore the need for proactive adaptation measures involving key stakeholders like farmers and policymakers (Büntgen et al. 2021). Furthermore, in 2021 we witnessed widespread damage to various crops, including fruit trees, across Europe due to frost and freezing temperatures. Late frost events have become more frequent over the past four decades (Lamichhane 2021).

Adaptation does not occur in an institutional vacuum (Agrawal and Perrin 2009). These climate impacts influence the complex dynamics of human-environment systems, in which past actions shape the very conditions we must then adapt to. The adoption of adaptation measures depends on the social and economic endowments of the subjects in question. A deeper understanding of these dynamics is essential to making informed decisions that avoid increasing vulnerabilities and diminishing our capacity to adapt. Effective adaptation and mitigation strategies require not only an understanding of the causes and consequences of climate change but also a willingness to modify behavior (Niles and Mueller 2016). The decision-making process in this context is multifaceted, involving factors such as farmers' beliefs, knowledge, economic considerations, and the perceived risks and opportunities associated with various adaptation and mitigation strategies (Chatrchyan et al. 2017). According to Fishbein and Ajzen (2011), behavior is shaped by numerous background factors that influence beliefs, which in turn shape attitudes, intentions, and ultimately, behavioral changes.

Understanding farmers' behavior is critical for maintaining food production under the diverse pressures faced by local agricultural systems. This understanding is essential for identifying areas where interventions are needed and for developing effective policies that promote socio-technical change and innovation (Feola et al. 2015). For example, in response to these risks, cropping system changes have demonstrated substantial adaptation benefits, including increased net farm income in the United States (Prato et al. 2010). Similarly, in Europe, improving irrigation scheduling, crop mix changes, use of new crop varieties, and improving irrigation efficiency, among other measures, have significantly contributed to drought adaptation (Kahil et al. 2015). With respect to frost adaptation, frost protection sprinkling has proven to be very effective as an adaptation measure (Unterberger et al. 2018).

Despite the heightened vulnerability of perennial crops to climate change due to their long life span, path dependencies, and the challenges associated with switching crops – primarily due to the high costs involved – there is a notable gap in the literature regarding the uptake of climate adaptation options within the perennial crop sector. Furthermore, farmers often face inadequate access to information and knowledge about climate change adaptation. Therefore, the goal of this paper is to examine the relationship between climate perceptions and adaptation behaviors among Swiss fruit farmers. In addition, we explore climate impacts on these perennial crops, focusing on frost and drought events. Farmers, as key stakeholders, face these challenges, necessitating adaptive strategies. Emphasis is on the long-term perspective of farmers dealing with perennial crops, recognizing the intricate nature of their decision-making and addressing a current gap in evidence related to factors influencing adaptation choices for perennials (Gunathilaka et al. 2018). To bridge this gap, we conducted a comprehensive survey to explore farmers' perceptions and expectations concerning climate change.

This paper contributes to the literature on climate perception and adaptation by examining the under-researched area of perennial crops and the role of personal beliefs in shaping farmers' responses to climate change. By addressing both drought and frost impacts, farmers' climate perceptions, beliefs, and expectations, alongside analyzing farmers' willingness to adapt and their policy support, we provide a cohesive analysis of farmers' behavior. This nationwide study offers unique insights into Swiss farmers' perceptions and adaptive strategies.

We observe that frost has a more pronounced impact on farmers' yields compared to drought. Interestingly, drought conditions can lead to some beneficial side effects, such as a reduction in fungal infestations and decreased pest pressure. Established mechanisms for preventing the effects of drought and frost are already very effective; however, there is room for improvement. Moreover, our findings indicate that farmers are generally more adept at identifying temperature trends than at correctly recalling frost or precipitation trends. Those farmers with fixed irrigation systems demonstrate significantly better accuracy in recognizing shifts in precipitation patterns. The majority of respondents express concerns about climate change, acknowledging a rise in global average temperatures. As expected, farmers categorized as climate change skeptics are less inclined to support government policies and environmental regulations than those who believe in anthropogenic climate change; however, unexpectedly, skeptics demonstrate a higher willingness to adapt. There are several possible explanations: farmers who believe that climate change is real and human-induced may feel disillusioned, leading to a lower willingness to adapt. Alternatively, they may have already implemented substantial adaptations in the past, which could reduce their current willingness to adopt further measures.

This paper is structured as follows: in Section 2.2 we provide a review of the relevant literature; Section 2.3 presents the survey content and results, including analyses of farm and farmer characteristics, the effects of drought and frost, adaptation behaviors, farmers' climate perceptions, expectations, and beliefs, their willingness to adapt, and their level of policy support. Finally, in Section 2.5, we discuss the findings and offer concluding remarks.

2.2 Related Literature

Existing research on the impact of climate change on agriculture highlights significant challenges to farmers' livelihoods. Intense summer heat waves and drought events of 2003, 2015, and 2018 had profound impacts on Europe's agricultural sector. These climatic extremes resulted in reduced harvests, increased insect outbreaks, and plant mortality (Büntgen et al. 2021). In addition to the challenges due to drought, certain sectors of agriculture, i.e., horticulture, are significantly threatened by spring frost. For instance, the unprecedented spring frost event in late April 2017 caused considerable damage to crops (Vitasse and Rebetez 2018). Similarly, in April 2021, late spring frost and freezing caused severe damage to fruit trees and other perennials (Lamichhane 2021). Farmers are directly affected by these events, often facing immediate yield losses and crop damage. Broomell et al. (2015) note that personal experiences with climate change strongly influence the endorsement of specific mitigation efforts, distinguishing between impact-oriented actions and general intentions to act, finding higher agreement with regard to engagement in general actions as opposed to specific impact-oriented actions.

The literature on farmers' perceptions of climate change and their adaptive behaviors is extensive and growing. Studies such as Fosu-Mensah et al. (2012) analyze farmers' climate perception and identify key factors for adaptation strategies of farmers in Ghana. They find strong climate awareness among farmers. Furthermore, they find that access to extension services, credit availability, soil fertility, and land tenure positively impact adaption. Despite recognizing the need for adaptation, a lack of funds often impedes the necessary adjustments. Similarly, research in the Sahel region highlights farmers' awareness of climate variability, particularly regarding the damaging effects of wind and excess rainfall, aligning with findings in Ghana (Mertz et al. 2009). Further studies, like Abid et al. (2019), reveal that farmers are generally more adept at recognizing temperature trends than precipitation changes, with accuracy in perception correlating positively with adaptive measures. Additionally, farming experience significantly increases the likelihood of adopting adaptation strategies. Arbuckle Jr et al. (2015) directly link climate perception and adaptation behavior and found that a majority of corn and soybean farmers in the U.S. believe in climate change; those holding such beliefs are more likely to support both adaptive and mitigative actions, including government intervention to reduce greenhouse gas emissions. In California, Haden et al. (2012) found that local climate concerns primarily motivate adaptation among farmers, while climate beliefs have a more substantial impact on the intention to adopt mitigation practices. Niles et al. (2016) concur, suggesting that these beliefs may influence the intended rather than actual adoption of climate practices.

Despite a growing body of research on climate-related risks, the literature on farmers' perceptions and adaptive behaviors remains uneven. While numerous studies have examined climate perceptions and adaptation strategies in the context of annual crops, fewer studies have addressed these issues in perennial crop systems. Perennial crop farmers face unique challenges and exhibit greater path dependency in adaptation practices, such as crop switching, compared to annual crop farmers (Nguyen et al. 2016). Gunathilaka et al. (2018) emphasize that adaptation practices for perennial crops often require more transformative changes, yet studies focusing on the intersection of climate perception and adaptation among these farmers remain limited. Our paper addresses this gap by examining farmers cultivating perennial crops.

Farmers' climate perceptions are not exogenous. Diving into a broader context, studies in New Zealand provide additional insights into how farmers' climate beliefs influence their perceptions and adaptation behaviors. Niles et al. (2015) observe that farmers who believe in human-induced climate change are more likely to perceive temperature increases, suggesting that personal and environmental factors play a significant role in shaping perceptions and following adaptation decisions. They highlight the importance of local context, with water scarcity and temperature variability emerging as critical factors in regions like Hawke's Bay and Marlborough, affecting adaptation strategies in viticulture and other sectors. Recent studies specifically on drought adaptation, such as the work by Zappalà (2024) in Bangladesh, reveal that prior beliefs significantly influence irrigation decisions in response to dry shocks, though the author cautions that these findings may be spurious. As these effects are dependent on the geographical context, the relationship between climate beliefs, perceptions, and adaptive behavior requires further exploration. We add to this by further including another geographical dimension, which will contribute to identifying similarities or discrepancies across different locations.

There is limited research in Switzerland examining the impact of climate change on farmers' adaptation strategies. Kruse et al. (2015) surveyed fruit growers in northeastern and northwestern Switzerland, finding that while drought-related damage has been limited, there is an expectation of more frequent and intense droughts in the future. A majority of farmers have already started implementing adaptive measures, like irrigation and mulching, which could be a reason why drought-related damages have been negligible. The study focuses primarily on drought, neglecting other extreme events like frost. More on the behavioral side, Kreft et al. (2021) explored the role of non-cognitive skills in adopting climate-mitigation practices, finding that traits such as self-efficacy and locus of control are crucial in determining the extent of such adoption among Swiss farmers. These studies underscore the importance of understanding regional variations in climate change impacts and the role of psychological factors in shaping adaptation strategies.

In summary, this paper adds to the existing literature on climate perception and adaptation behavior by exploring under-researched geographical dimensions, and the role of personal beliefs in influencing farmers' responses to climate change. A key contribution of this study is its focus on perennial crops, an area that has received limited attention in prior research. Additionally, by addressing both the impacts of drought and frost, as well as investigating farmers' climate perceptions and willingness to adapt, we are able to integrate several strands of literature, creating a more cohesive image. A significant contribution of our work is the development of a new "Willingness to Adapt Index" and a "Policy Support Index", which measure farmers' readiness to implement adaptive measures and their support for climate-related policies. To the best of our knowledge, there is no nationwide study in Switzerland that examines farmers' views and adaptation decisions related to climate change, particularly with a focus on perennial crops. Our research fills this gap, offering valuable insights into the perceptions and adaptive strategies of Swiss farmers in response to climate variability.

2.3 Survey

An essential approach to extract otherwise invisible factors, such as perceptions and beliefs are surveys (Stantcheva 2022). Hence, to elicit farmers' individual characteristics, farm infrastructure, climate perceptions, and beliefs, we conducted an online survey using the Qualtrics platform. Online surveys have many advantages such as the flexibility of the target group to complete the survey at their convenience. As farmers in Switzerland are required to fill out administrative documents received by e-mail, the coverage error will be minimal.[12]

The creation of the survey was implemented in several feedback loops. A first draft of the survey was created including parts of the surveys conducted by Kruse et al. (2015) and by Niles and Mueller (2016). Feedback in multiple rounds was gathered by local producers, employees of the Swiss Fruit Association SOV, Agroscope, the Swiss Confederation's center of excellence for agricultural research, and Agridea, the center for Agricultural Advisory and Extension Services. Upon completion, the survey was translated into French, ensuring availability in both German and French. The survey was then distributed via e-mail to approximately 1800 fruit farmers, more precisely all fruit farmers in Switzerland, cultivating more than 20 acres of orchards. The survey period extended from May to December 2022. To encourage participation, respondents were offered the chance to win one out of 15 Landi[13] vouchers in the amount of CHF 100.[14] In

[12]The *coverage error* is the difference between the potential pool of respondents and the target population (Stantcheva 2022). Hence, an online survey can only be filled out by people having a phone/computer and internet access.

[13]Landi being one of the largest agricultural retailers in Switzerland

[14]There is still some risk of a selection bias in the respondents. People responding to the survey might share some specific characteristics.

total, we received 547 responses, which equals a response rate of 28.9%. From those, 127 responses were dropped due to insufficient data, leaving 420 responses (22.2%).

Table 14: Survey Content and Structure

	Thematic block	Questions aimed at
A	Questions about the farm	Type of fruit, acreage, distribution, irrigation system and amount of irrigation, source of water
B	Questions about the effects of drought on fruit growing	Impact due to drought in the last 10 years (+/−), financial loss, adaptation measures, effect of years 2015 and 2018, willingness to adopt new measures if extreme years occur more often
C	Questions about the effects of frost on fruit growing	Impact due to frost in the last 10 years (+/−), financial loss, adaptation measures, effect of years 2017 and 2021, willingness to adopt new measures if extreme years occur more often
D	Questions about their assessment (climate perception, beliefs)	Agreement/disagreement (agree ∣ somewhat agree ∣ somewhat disagree ∣ disagree ∣ don't know) with several statements regarding drought, frost, and climate change, perception of weather change over time, concern about several climate-related risks and future impacts, general opinion about the government, public policy, and agriculture, risk-averse/loving
E	Closing questions (individual characteristics)	Gender, age, experience, education, category of farm (full-time farm, etc.), membership of SOV

Notes: The survey begins with a section covering standard farm characteristics. This is followed by two nearly identical sections focused on the effects of drought and frost, respectively, on fruit growing. The subsequent section includes assessment questions, primarily using agreement/disagreement and Likert scales, to elicit respondents' climate perceptions, beliefs, and opinions on policy and government. The survey concludes with questions about individual characteristics.

The content of the survey consists of 5 different question blocks A–E (see Table 14). The first section contained questions about farm characteristics. This was followed by two nearly identical sections that focused on the impact of drought respectively frost on fruit cultivation. These sections included inquiries about financial losses, current adaptation measures, and willingness to adopt new strategies. The next section explored the farmers' perceptions, expectations, and beliefs regarding climate change, as well as their general views on the government, environmental regulations, and risk preferences. Risk perception is assessed following the methodology outlined by Dohmen et al. (2011). The last section concluded with questions about individual characteristics.

2.4 Methods and Results

2.4.1 Farms' and Farmers' Characteristics

From the 420 responses, the largest group (27%) originated from the canton Thurgau. The second biggest contributor (10%) is the canton Aargau. The distribution over the different cantons in percentages can be found in Figure 29 in the Appendix. The average age of the respondents is around 50 years, where the oldest respondent was born in 1922 and the youngest in 1998. The majority of respondents are between

45 and 60 years old. Years of experience range from 1 to 97 years, with a mean of 28 years. 95% of the respondents are male. Most of the farmers grew up in agriculture and then proceeded by either doing an apprenticeship, going to farm management school, and doing a master's, or a combination of those. Almost half of the respondents went on to get further qualifications in fruit growing, such as taking a tree pruning course, courses in organic farming, or specialty courses for stone fruit and pomes. Additionally, as can be seen in Figure 31 in the Appendix, farmers have a tendency to be more risk-loving than risk-averse.

Regarding the farm category, 81% of farmers run a full-time farm, meaning that the non-farm income of the farm manager is less than 10%. About 10% run a part-time farm with 10–50% non-agricultural income and 8% with non-agricultural income above 50%. Only 1% operate a "recreational farm", in which the farm income is an insignificant part of total income. 86% of the respondents are members of the Swiss Fruit Association (SOV). When asked about the percentage of fruit growing as part of their agricultural income, around 40% of the farmers attribute more than 50% of their agricultural income to fruit growing.

The average farm size is 1,579 ares, equivalent to 157,900 m^2. Farm sizes range from 24 to 120,000 ares, with 75% of respondents managing farms smaller than 678 ares. 43% distribute their products through wholesalers such as Fenaco and Tobi, and 34% through direct sales, farm stores, market stalls, or the like. About 5% of the farmers sell through wholesalers such as Migros, Aldi, Lidl or similar. 9% use a local or regional distributor such as Landi and the remaining 5% use other distribution logistics.

Of the 420 respondents, 341 grow pome fruit, 311 stone fruit, 87 berries, 34 nuts, and 22 other fruits. The majority of fruit growers plant not only one crop but several. It follows that both pome and stone fruit are the crops that produce the greatest economic yield for the farmers.

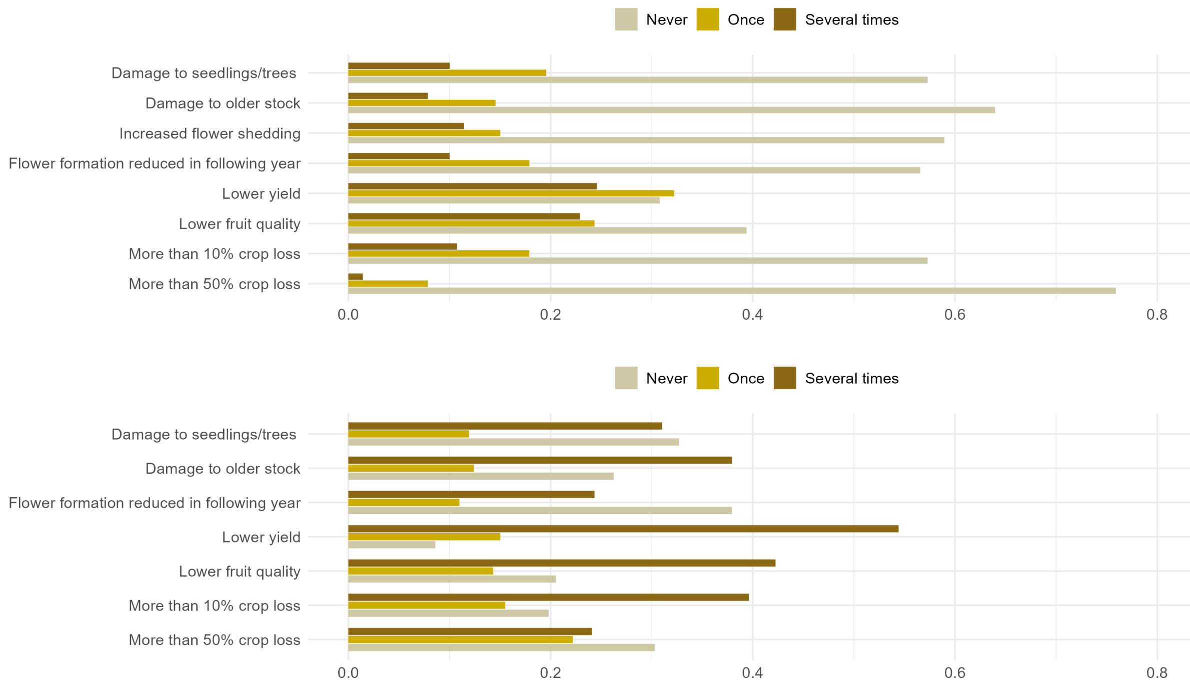
When planting crops, 65% of the respondents take site-specific characteristics into account, like soil conditions, topography, and geographic targeting. Those who consider site-specific characteristics mostly evaluate soil conditions, frost vulnerability, and, in general, resistance of crop, the closeness of water source, and topography (often gradient and geographical targeting).

2.4.2 Effect of Drought and Frost on Agricultural Yield

When examining the impact of drought and frost on the orchard over the past decade, it becomes evident that frost has inflicted more significant damage compared to drought. Figure 20 illustrates the harm caused by both dry spells and frost. Across all damage categories, a larger proportion of farmers have reported damage attributed to frost compared to damage caused by dry spells.

Consequently, financial losses over the last 10 years are larger because of frost than because of drought, where the mean loss as a percentage of the average agricultural income from the fruit-growing branch of the business over the last 10 years is 7.5% from drought and 20.7% from frost. Potential measures against drought are irrigation, soil cultivation (e.g., hoeing, loosening), ground cover (e.g., mulching, overgrowth), shading, and cultivation of drought-resistant fruit crops, whereby in Switzerland mainly irrigation and ground cover are used (Kruse et al. 2015). We observe in our sample that the majority (64%) uses irrigation as a measure against drought. Around 43% use ground cover to protect against drought, 15% use tillage, and 8% use shading. The aforementioned countermeasures have demonstrated significant effectiveness in mitigating the impacts of drought. On average, they enabled 60% of the respondents to prevent 20% of the losses over the past 10 years that would have occurred in the absence of such measures.

Figure 20: Climate Damages



Notes: Occurrences of several potential damages as a result of dry spells (top) or frost events (bottom) on the farmers' orchards over the last 10 years. Farmers were given the possibility to answer with respect to each potential damage, and answer options were "Never", "Once", or "Several times".

In terms of potential measures, the literature shows that there is a wide range of potential on-farm mitigation strategies (e.g., increasing productivity and efficiency, specific technology, adapting farm management (Kreft et al. 2021)). Regarding fruit production, irrigation infrastructure is arguably the most important measure that farmers use to protect against climate impacts, as it is used to address both frosts and droughts. In theory, irrigation can be divided into two broad groups, total surface irrigation, and local irrigation, which in turn can be divided into two groups (see Figure 30 in the Appendix). Whole surface irrigation can be either overcrown irrigation or undercrown irrigation, while local irrigation is either microjet irrigation or drip irrigation (Monney and Bravine 2011).

Of the fruit growers surveyed, 140 do not irrigate their crops, while 218 use a fixed irrigation infrastructure, though fewer than half of these irrigate all of their fruit crops. Those who irrigate part of their crops with a fixed infrastructure irrigate, on average, 55% of the crops. 78 growers irrigate with a mobile device or by hand and do not have a permanently installed irrigation system. Overall, around two-thirds of the respondents irrigate. The average size of farms that irrigate is more than twice as large compared to farms that do not irrigate. From our survey data, the majority of participants with fixed-installed irrigation systems (188) irrigate their crops with drip irrigation. 43 participants use a microjet irrigation system, 41 rely on an overcrown irrigation infrastructure, and 41 use sprinklers. Some participants rely on more than one system. Most participants get water from either groundwater or water reservoirs. Fewer rely on water supply from lakes or rivers. Almost 90% of the respondents do not have contracts with the municipality to secure water supplies from the drinking water network. The minority that has a contract is spread over most of the cantons and not concentrated in one canton.

In our case, there is no significant difference in the effectiveness of the irrigation systems used by the farmers in preventing yield loss attributed to drought. This does not necessarily mean that they all perform similarly but that the farmers are good at selecting the system that works best in their respective environments. The mean financial percentage loss of yield does not show statistically significant differences. The losses are slightly higher for partial irrigation and hand irrigation as opposed to complete and fixed irrigation and are the highest for farmers who do not irrigate at all.

In response to late spring frost, potential measures are overhead irrigation[15], heating (frost candles)[16] and air circulation (wind and blower machines)[17]. Out of the chosen answers, most farmers respond to frost by using frost candles (39%). Only 13% of respondents use irrigation as frost protection and about the same percentage have insurance against frost damage. In addition, many farmers use foil coverage of the crops.

Irrigation is more frequently employed as a countermeasure in response to drought compared to frost. On average, farmers use irrigation for 30 days during drought conditions, with 90% of cases requiring fewer than 82 days of irrigation. Conversely, for frost events, farmers typically irrigate for only one day, with 90% of occurrences necessitating fewer than 5 days of irrigation. Protective measures against frost have proven effective in at least a third of instances, resulting in an average prevention of 30% of financial losses.

Regarding positive effects, the majority of farmers (57%) expressed the view that drought periods have had a beneficial impact on fruit growing. This positive effect is primarily attributed to reduced fungal infestations, diminished requirements for pest management, and lowered disease pressure.

As mentioned, the years 2015 and 2018 were particularly challenging for farmers due to drought, while intense spring frost events in 2017 and 2021 presented additional threats. To explore the impact of these specific years, farmers were surveyed and asked to indicate which of these years had the most detrimental effect on their operations. When comparing the impact of extensive drought over two years (2015 vs. 2018), 2018 had a more substantial influence. Approximately two-thirds of respondents reported experiencing greater losses in 2018. Nonetheless, the majority of them still incurred no more than a 10% reduction in their harvest. Regarding frost, 2017 was a more challenging year compared to 2021 for over two-thirds of all farmers, with nearly 50% of them losing more than half of their yield. As a response to April 2017, immediate measures were implemented by federal and cantonal authorities, as well as agricultural organizations, including deferrals on loan repayments, interest-free loans, and investment credits. There was also the option of direct payments for frost-damaged areas, and Fondssuisse[18] provided additional support for severe cases. Eligibility for short-time work compensation was clarified. In our sample, 20% of the farmers received direct payments as a result of this particular frost event. The average total payment (not per ha) in 2017 was just short of 60,000 Swiss francs, whereas in 2021, it was around 25,000 Swiss francs.

[15]Water releases heat to its surroundings when it freezes. As water freezes directly on the plants, the heat benefits the plant parts. The system must be switched on before the wet bulb temperature falls below the critical plant temperature.

[16]The air is heated with fire. Tin buckets with kerosene are distributed in the plant area before the frost night and lit with a burner before the temperature falls below the critical temperature.

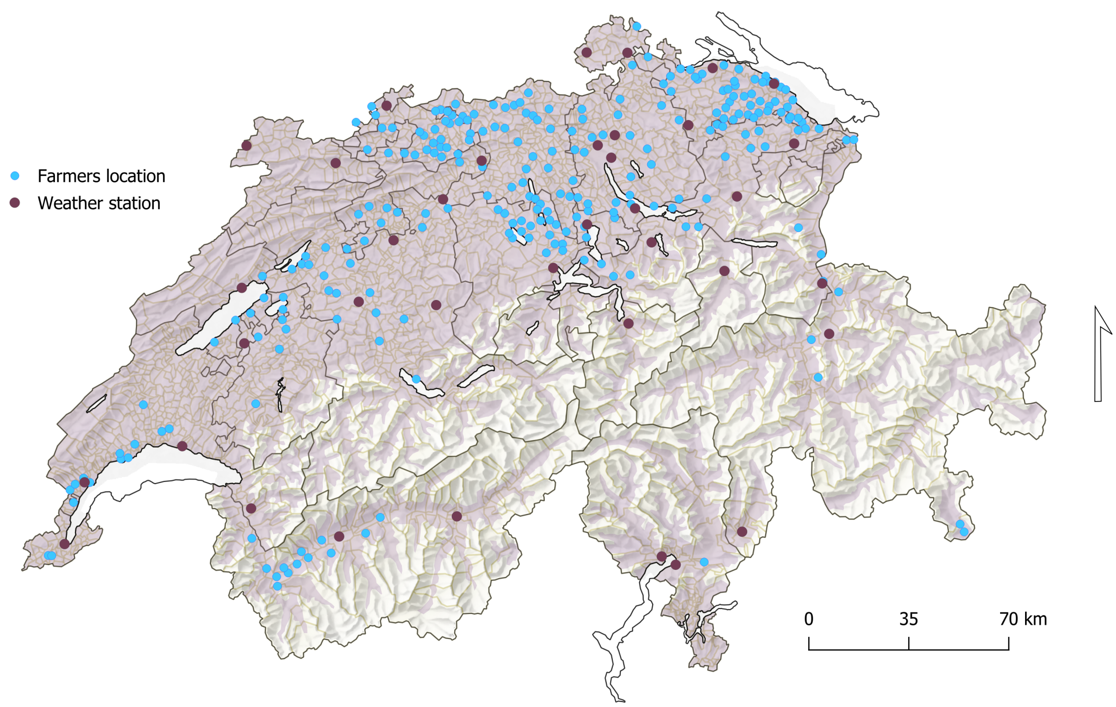
[17]By circulating the air layers, warm air from higher layers enters the system.

[18]Fondsuisse is a foundation that provides financial support for damages caused by unforeseeable natural events, for which no insurance coverage can currently be obtained.

2.4.3 Climate Perceptions, Expectations, and Beliefs

In order to evaluate the accuracy of climate perceptions, we compare historical weather data to farmers' perception of changes in summer temperature, winter temperature, annual precipitation, number of heat days per year, number of frost days per year, frequency of drought, and frequency of heavy precipitation events. MeteoSchweiz, the Federal Office of Meteorology and Climatology, provides weather data such as precipitation and temperature (daily average, daily minimum, daily maximum) from ground monitoring stations across Switzerland spanning the years 1980–2022. Geocoding, using Google Geocoding API, was employed to match longitude and latitude to all farmers' locations as well as weather stations (see Figure 21). Subsequently, we assigned to each farm location the geographically closest weather station. All 37 weather stations were chosen and matched by a minimum distance.

Figure 21: Geographical Locations



Notes: Map of Switzerland showing the location of all geocoded farmer survey respondents (blue) and weather monitoring stations (red).

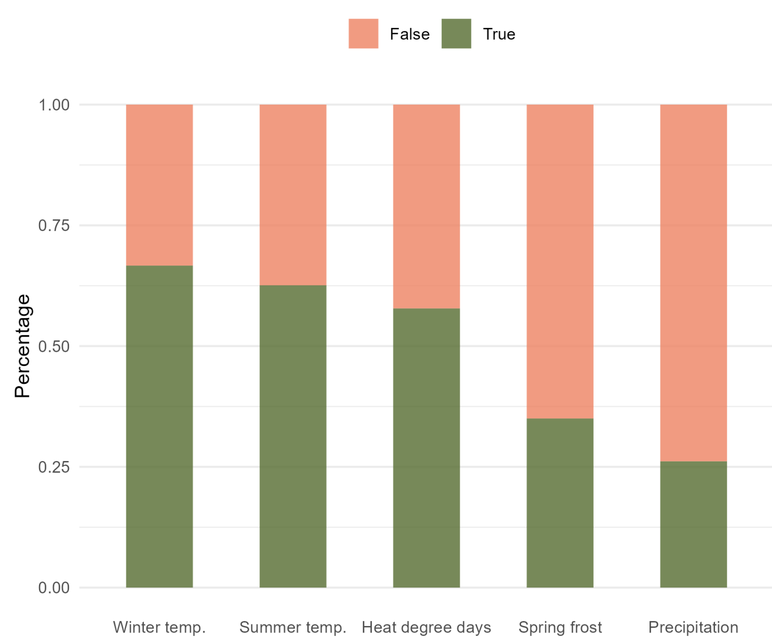
Table 16 in the Appendix shows the climate trend over the years 1981–2019 per station for the variables winter temperatures (DJF), summer temperatures (JJA), precipitation, spring frost days ($\leq -1°$C in MAM), and heat degree days (number of days above 30°C). Overall, summer temperatures, winter temperatures, yearly mean temperatures, and heat degree days have increased. The trend over the years per station for frost days and precipitation is not as clear. Averaging over all the stations, these two variables have slightly decreased.

Subsequently, we constructed individual climate trends for these same variables based on the time frame relevant to each farmer's agricultural career. Farmers provided perceptions of changes in various climatic variables over their agricultural careers, indicating whether these variables increased, remained constant, decreased, or were uncertain. The weather trend was either positive or negative, significant or insignificant. By juxtaposing weather trends with farmers' perceptions within each canton, individual true and false values were derived. If the individual weather trend for the respective climate variable was insignificant, the farmers were correct (getting a "true" value) by either identifying the right trend or if they were uncertain. If the trend was significant, however, the farmers were only correct by identifying the increase or decrease over time.

Climate Perceptions

We can see in Figure 22, that farmers are more accurate in their assessment regarding temperatures and heat degree days. They are, however, more often wrong than right when it comes to spring frost and precipitation. This could be due to the fact that the climate trends for temperatures and heat degree days are, in fact, clearer and have been discussed in the media to a large extent. An additional factor could be that the potentially large impact of spring frost on yield may contribute to an inflated perception of their frequency, whereas the comparatively easier adaptability to droughts leads to an underestimation of their occurrence. The mean frost damage reported by farmers who accurately perceived the spring frost trend is slightly higher than that of farmers whose perceptions were incorrect. However, this difference in means is not statistically significant.

Figure 22: Farmers' Perceptions of Past Trends



Notes: Visualization of farmers' perception of the development of spring frost, heat degree days, precipitation, summer temperatures, and winter temperatures in their region over time, categorized by perceived accuracy. The figure shows the proportion of respondents who were right (True) or wrong (False) in their individual perception of each weather trend.

With respect to other environmental perceptions, a significant majority of farmers have reported an increase in pest infestations over time. In contrast, water availability is generally perceived as stable. These findings, along with farmers' responses to various climate and environmental perceptions, are illustrated in Figure 34 in the Appendix.

To further explore farmers' perceptions of precipitation, we categorized respondents according to their irrigation methods. Initially, we divided farmers into two groups: those using fixed irrigation systems and those with no irrigation systems. Farmers using fixed irrigation systems, either fully or partially on their crops, and those using mobile irrigation systems were clustered together. We then matched these groups with the logical variable of their precipitation trend estimation (TRUE/FALSE), as previously described. Combining these two TRUE/FALSE variables, we get the count of correct estimations within each group to assess the accuracy of their predictions. Subsequently, a statistical comparison was conducted, employing a Chi-squared to determine whether significant differences existed among the three groups ($p = 4.582e^{-06}$). We find that farmers employing an irrigation system are significantly more accurate in detecting the predominantly negative trend in yearly precipitation. Subsequently, we divided the farmers into three distinct groups: fixed irrigation, mobile irrigation, and no irrigation system. Significant differences between these three groups persisted ($p = 4.606e^{-07}$), with the fixed-irrigation group achieving the highest accuracy. Interestingly, the group without any irrigation infrastructure outperformed the group with a mobile or hand irrigation infrastructure. These results become even more pronounced when restricting the analysis to full-time farmers, who made up the majority of survey participants. Among full-time farmers, the group with fixed irrigation infrastructure has more than twice as many correct precipitation perceptions compared to the group with no irrigation infrastructure, and more than five times as many correct perceptions compared to the group with mobile irrigation infrastructure.

Climate Expectations

In addition to providing meteorological data from its network of weather stations, MeteoSwiss developed the Swiss Climate Scenarios CH2018, which are climate projections derived from regional climate simulations. These projections are based on various emission scenarios known as Representative Concentration Pathways (RCPs), which model different potential climate futures. Among the most significant projected changes are those related to extreme weather events. Notably, the frequency, intensity, and duration of heatwaves and extremely hot days are expected to increase. Summer temperatures are projected to rise by approximately +2.5°C to +4.5°C, with the longest dry periods in summer extending by up to +9 days. The number of very hot days, currently averaging one per summer, could increase by 3 to 17 days. Additionally, the temperature of the hottest day of the year is likely to increase by +2°C to +5.5°C. Winter temperatures are also expected to rise, with projections indicating an increase of +2°C to +3.5°C. Consequently, there will be fewer and less intense cold waves, frost days, and ice days. These absolute changes will be more pronounced at higher elevations and are expected to be substantially larger in scenarios without climate change mitigation measures (CH2018 2018). However, these changes do not necessarily translate to a reduction in spring frost risk for fruit trees, as the projected climate changes lead to an earlier onset of spring. As Lhotka and Brönnimann (2020) indicate, this could result in increased exposure of vegetation to spring frosts in Switzerland. Furthermore, heavy precipitation events are anticipated to become more frequent and intense in all seasons, with a more pronounced effect during the winter months. The changes in summer precipitation are less certain, with projections indicating a range from a 25% decrease to a 10% increase (CH2018).

As depicted in Figure 33 in the Appendix, respondents were asked to share their views on statements related to drought and frost. The analysis indicates a widespread agreement among farmers regarding the expectation that "Drought will occur more often in Switzerland in the future compared to the past". When it comes to the same statement about frost, they only somewhat agree. Hence, farmers expect more droughts than frost events in the future, which is in line with climate projections, not taking into consideration that frost risk could still increase through a shift in the growing season. Furthermore, a significant number of farmers believe that future drought periods will be longer, and they anticipate adverse effects on their farms due to drought. Despite these concerns, farmers remain hesitant to invest in infrastructure such as irrigation ponds or wastewater reuse facilities. There is relatively less reluctance when it comes to investing in fixed irrigation systems, though farmers are still generally unwilling to take out loans for such investments. This hesitation is even more pronounced in the case of frost adaptation, with the majority of farmers expressing no willingness to invest in irrigation systems, heat, and fan machines, or to take out loans to finance frost-related infrastructure. Nevertheless, farmers are open to enhancing their knowledge of appropriate management strategies should the frequency of frost or drought increase in the future.

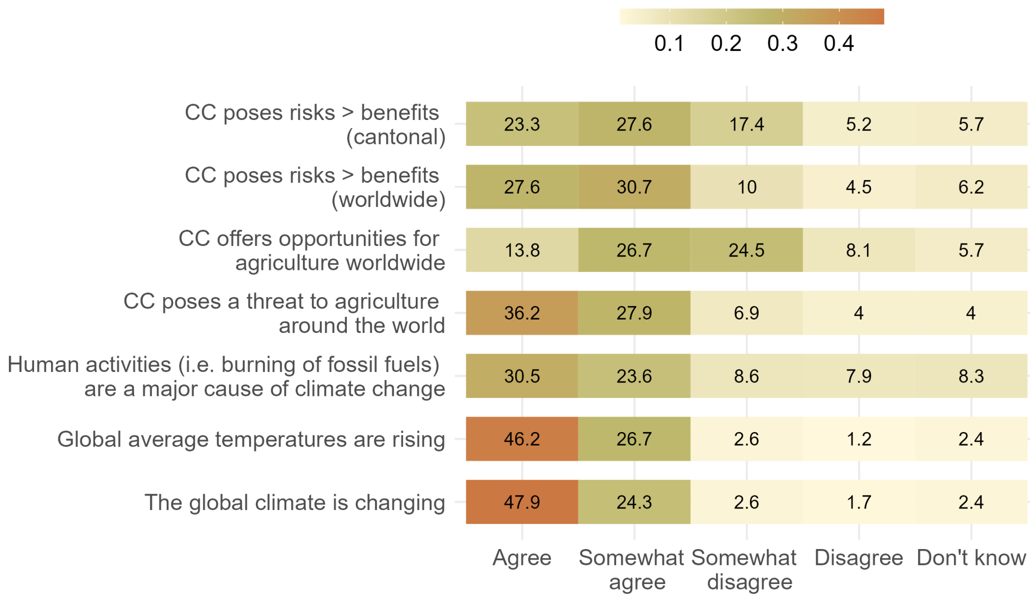
Climate Beliefs

In line with assessing climate expectations, farmers were surveyed about their general opinions on climate change. They were asked to agree or disagree with statements regarding whether climate change presents more risks than benefits, whether it poses a threat to global agriculture, whether it is anthropogenic, and their overall stance on global warming. As illustrated in Figure 23, a significant majority of respondents expressed concerns about climate change, acknowledging the rise in global average temperatures and the shifting global climate. Many perceive climate change as a potential threat to agriculture.

Using the respondents' view on climate change, we created the following four farmers typologies based on Niles and Mueller (2016): (1) belief that climate is changing and humans are contributing; (2) belief that the climate is changing but humans are not contributing; (3) belief that climate is not changing and humans do not contribute; (4) belief the climate is not changing, but humans contribute to climate change. We excluded belief Type 4 from the analysis due to its limited representation with only one observation. Farmers were categorized into these groups based on their responses to the specific statements previously outlined and shown in Figure 23. Those affirming either "The global climate is changing" or "Global average temperatures are rising" alongside agreement with the statement "Human activities such as the burning of fossil fuels are an important cause of climate change" were assigned to Type 1. The first two statements serve as indicators of climate change belief, while the third statement proxies human contribution perceptions. Farmers who endorsed the first two statements but not the third were categorized as Type 2, and so forth. Farmers who didn't fit any of the categories or answered with neither agreement nor disagreement but with "Don't know" were classified as missing. We hypothesize that farmers who acknowledge climate change are expected to be more attuned to climate patterns than those who deny or attribute climate change to non-human factors.

The correlation matrix, seen in Table 15, reveals associations between belief typologies and weather perceptions. Notable findings include the moderate positive correlations between Type 1 beliefs and being right in their climate perception. Being of Type 1 and having a better climate perception seems to be associated more than with the other types. These results underscore potential patterns in how individual belief sys-

Figure 23: Farmers' Perceptions on Climate Change



Notes: Farmers' views on global climate trends, causes, and impacts on agriculture, and opportunities and risks posed globally and locally. The legend indicates the percentage of farmers selecting the individual response possibilities.

tems may be linked to their perceptions of specific weather conditions, providing insights into the interplay between cognitive frameworks and environmental interpretations. Type 2 and Type 3 are similar in their correlations with respect to having correct perceptions. They differ in their view of climate change but agree that humankind is no major cause. However, the correlational nature of the analysis cautions against inferring causation or complex dependencies. These results are robust when using regional weather data instead of weather station data as a basis for the perception indicator.

Table 15: Correlation Matrix

	Type 1	**Type 2**	**Type 3**
Summer Temperature	0.251	-0.179	-0.224
Winter Temperature	0.089	-0.042	-0.147
Precipitation	0.094	-0.100	-0.027
Heat Days	0.175	-0.090	-0.246
Frost Days	-0.028	0.073	0.094

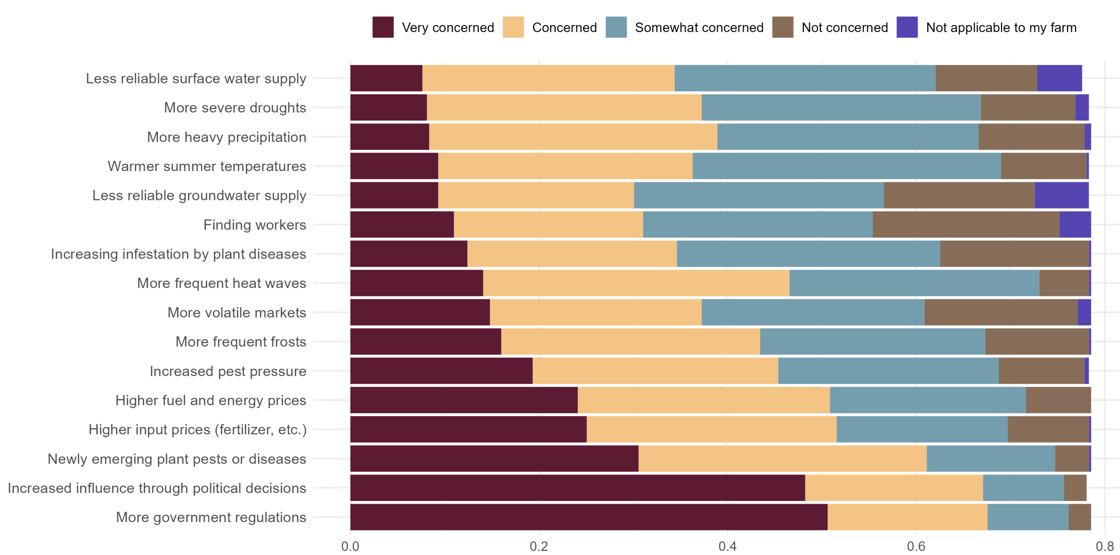
Notes: Correlation matrix illustrating the relationships between having a correct climate-related perception (Summer Temperature, Winter Temperature, Precipitation, Heat Days, and Frost Days) and the three belief types (Type 1, Type 2, Type 3).

Further inquiry is needed to explore additional underlying character traits that may influence this context. Additionally, it is crucial to examine whether experiences with frost or drought have had an impact on the observed patterns.

2.4.4 *Policy Support*

To assess the perceived urgency of climate-related issues among farmers, we surveyed them regarding their concerns about climate risks and other factors that could potentially affect their farming operations over the course of their careers. Our findings indicate that farmers in Switzerland are primarily concerned with increased government regulations and heightened political influence, rather than the potential exacerbation of severe droughts or the increased frequency of frosts. Figure 24 visually depicts a ranking of respondents' concerns related to climate risks and future impacts. The data reveal that the two issues eliciting the highest levels of concern – where most respondents indicated they were "very concerned" – are increased government regulations and the growing influence through political decisions. High on the list of concerns are also rising input costs, including higher fuel and energy prices. Pests and diseases emerge as significant concerns, alongside governmental and economic factors. This concern may be diminishing, as many respondents have reported a decline in pests and diseases attributed to droughts and generally drier climate conditions. Among climate-related issues, the most pressing concern for farmers is the potential for more frequent frosts, followed by more frequent heat waves. Overall, the survey results suggest that climate risks are relatively low on the list of priorities for the respondents.

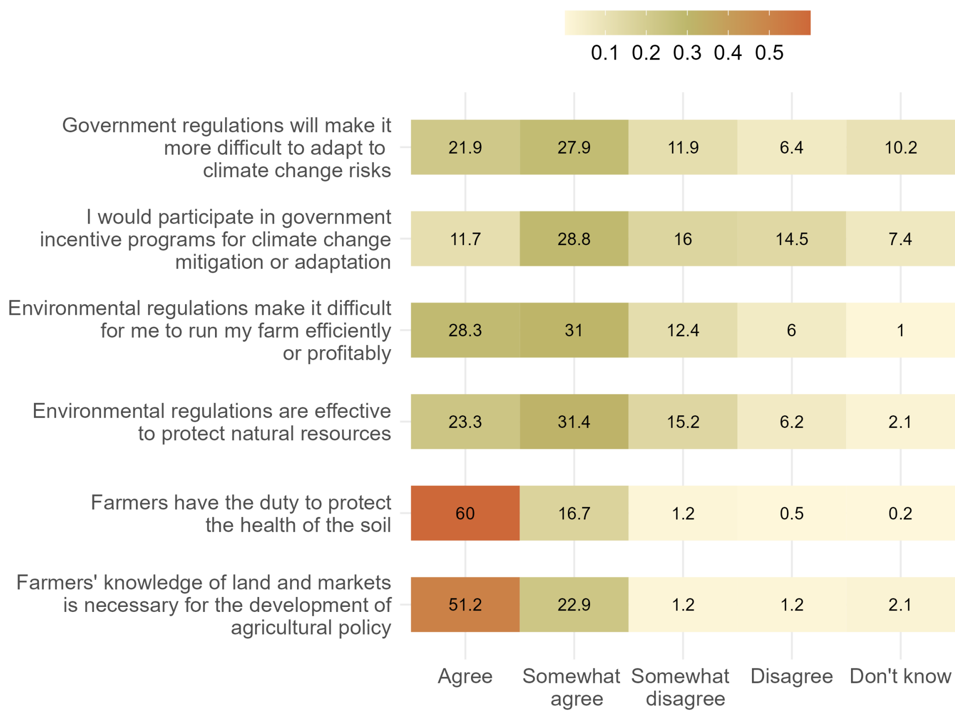
Figure 24: Farmers' Concerns



Notes: Farmers' concerns about climate-related and other risks that could impact their farming operation during their careers. The level of concern ranges from "Not concerned" to "Very concerned". On the bottom is the issue that most farmers are "very concerned" about.

Along these lines, we included a question to assess the level of policy support among farmers. Responses to several statements concerning environmental regulation, government incentive programs, and the environmental responsibilities of farmers are presented in Figure 25. These responses were quantified on a scale from 1 (strong agreement) to 4 (strong disagreement), with an additional option for uncertainty. The statements were broadly formulated to address environmental policy in general, without referencing specific incentive programs or regulations, as our primary interest was in eliciting overall policy support.

Figure 25: Farmers' Policy Perspectives



Notes: Farmers' answers to a question aimed at understanding their perspective on agricultural policies. Assessing attitudes towards farmers' knowledge, environmental regulations, and the impact of regulations on farm efficiency and climate adaptation.

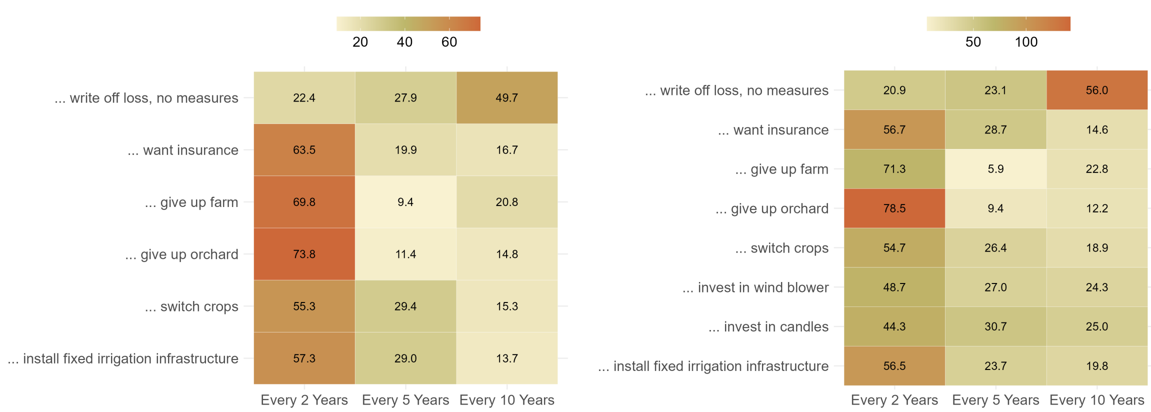
We chose four different statements to analyze policy support, namely "Government regulations will make it more difficult to adapt to climate change risks", "I would participate in government incentive programs for climate change mitigation or adaptation", "Environmental regulations make it difficult for me to run my farm efficiently or profitably", and "Environmental regulations are effective to protect natural resources". To accurately capture the sentiment of positively worded items reverse coding was applied. This ensured that higher scores uniformly indicated a greater endorsement of policy measures across all items. The cumulative scores from these four questions formed the Policy Support Index (PSI), calculated for each respondent. With four statements, each scored from one to four, the possible PSI values range from four to 16, with a mean of 9.52, a minimum of four, and a maximum of 16. Linking the PSI to belief typology reveals that Type 1 respondents exhibit the highest level of policy support with an average PSI of 9.96. Type 2 respondents show slightly lower support, with a mean PSI of 8.19, reflecting a less favorable view towards environmental regulations. Type 3, although the smallest group, demonstrated the lowest average support (mean PSI of 7.8), suggesting that this group is the least positively inclined towards policies aimed at environmental guidance. This result is to be expected as Type 3 is the more climate skeptic group compared to Type 1 and Type 2. When disaggregating the different statements, Type 1 remains the most policy-supportive group across all four statements.

Looking at the last two statements of Figure 25, both statements reveal strong positive attitudes among farmers regarding their responsibilities and the importance of their knowledge in agricultural policy-making. The high levels of agreement suggest that farmers are not only aware of their environmental responsibilities but also believe that their practical insights are vital for informed policy development.

2.4.5 Adaptation Behaviour

Following our insights into policy support, we examined how farmers' beliefs and attitudes shape their adaptive responses to climate events. In addition to the question about the impact in the years 2015/2018, and 2017/2021, as discussed in Section 2.4.2, the farmers were asked about how they would react if those events (droughts in 2015 and 2018, and frost events in 2017 and 2021) occurred at varying intervals: every 2 years, every 5 years, and every 10 years. There were several adaptation answer possibilities as well as two answer possibilities with exit strategies (give up the orchard, give up the farm). The adaptation possibilities for drought were to invest in insurance, switch crops, or install a fixed irrigation infrastructure. For frost, possible adaptation strategies were to invest in insurance, to switch crops, to invest in either a wind blower or in candles or to install a fixed irrigation infrastructure. We expect to see linear patterns, meaning that as the frequency of the drought/frost event increases, more farmers would choose adaptation options, and fewer farmers would just want to write off their losses. The same pattern was expected when looking at exit options. We expect that with increasing frequency of events, more farmers would be willing to either give up their orchards or give up their farms. The effects were expected to be more pronounced for frost, as frost impacts are larger and harder to adapt to. What is striking, however, is that there seem to be different preference patterns regarding adaptation versus exit strategies.

Figure 26: Adaptive Behavior



Notes: Farmers were asked to consider the scenario that a year resembling the conditions of 2015/2018 (for drought) or 2017/2021 (for frost) occurs with increased frequency in the future. The scenarios specified the frequency of occurrence as every 2, 5, or 10 years. They were then asked for each frequency of occurrence and which measures they would implement to combat drought (left) or frost (right). The selection of multiple measures simultaneously was allowed.

What we can see in Figure 26 is that farmers are consistent in their answers when it comes to adaptation strategies. If the frequency of heavy drought events increases from 10 to 5 and then to 2 years, farmers are continuously more likely to switch crops, want insurance, and install fixed irrigation infrastructure, and a decreasing fraction would simply write off their losses with no measures. As the frequency of frost events increases, more farmers would want to switch crops, invest in wind blowers, install fixed irrigation infrastructure, want insurance, invest in candles, and a declining fraction would want to write off their loss and not use any measures. These linear patterns are as expected. This linearity does not carry over to exit strategies. There seem to be U-shaped preferences. Farmers are more likely to exit (give up orchard/give up farm) when the frost or drought event occurs at either 2-year or 10-year intervals. As explained above, this result is unexpected. This result is more pronounced when looking at frost.

We examined the same question by dividing the sample into different age groups, as the age of the farmer could influence their long-term perspective. A farmer nearing retirement might choose to exit or adapt at certain time intervals rather than respond with a long-term strategy. We analyzed different age groups, specifically, ≤ 50 and > 50; ≤ 40 and > 60. The pattern, however, remained consistent across all groups. Therefore, age does not account for this particular pattern. We have explored other explanatory paths, but so far we have not been able to explain that phenomenon.[19] Further research is needed to understand the discrepancies between adaptation and exit strategies.

Willingness to Adapt

Using the same survey question (Figure 26), we categorized respondents' answers to the adaptation measures numerically, assigning a value of one to the two-year interval, two to the five-year interval, and three to the ten-year interval.[20] Based on individual answers to the adaptation measures, excluding exit options, we created an index reflecting the willingness to adapt (WTA).

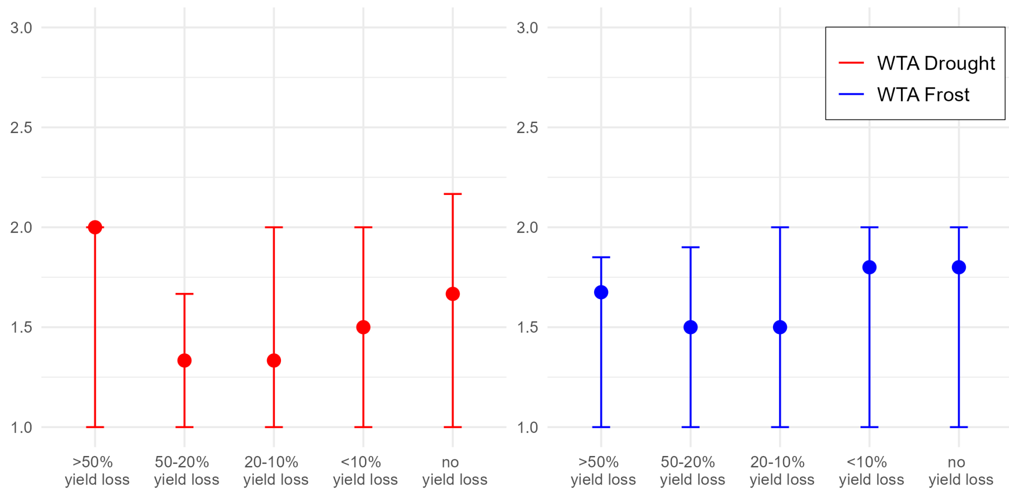
We identified the critical year for each farmer as the specific time threshold (2, 5, or 10 years) at which the farmer expressed readiness to implement adaptive measures. For instance, a farmer might be willing to invest in fixed irrigation infrastructure if a severe drought occurred every 5 years but would not make the same investment if this drought occurred only every 10 years. However, the farmer would also invest if it occurred every 2 years, making the "critical year" in this case 5 years. To quantify this willingness to

[19]Farmers who responded with a "13" (indicating both "every 2 years" and "every 10 years") were minimal, with only one farmer selecting this for both frost and drought, and these responses did not extend to the exit questions. Specifically, one farmer answered "13" for drought insurance and another for wind blower due to frost, indicating that this unusual response pattern is not driving the overall results. When focusing on farmers who consistently chose "3" (every 10 years) without selecting "1" (every 2 years), a more significant number of respondents followed this pattern. For instance, 22 farmers answered "3" at least twice for drought and 41 for frost, with 16 farmers overlapping between these two samples. Narrowing the focus to those who selected "3" at least three times reveals 17 farmers for drought and 23 for frost, with 11 overlapping. Among those who responded "3" exclusively to the exit questions, 16 farmers did so for both drought and frost, though only 8 overlapped. The number of missing responses per sub-question varied, indicating that while there are many missing data points, they are not systematically skewed toward any particular exit option. Regarding the belief typology of the overlapping farmers (see Section 2.4.3), among the 8 who answered "3" exclusively to the exit questions, 6 were of type 1, and 2 were of type 2. For the 11 farmers who chose "3" at least three times across all questions, 7 were type 1, 3 were type 2, and 1 was uncategorized. In the broader group of 16 farmers who selected "3" at least twice, 10 were type 1, 5 were type 2, and 1 was uncategorized. Interestingly, these farmers did not select multiple responses simultaneously, which might indicate a misunderstanding of the questions. To explore further, a filter was applied to identify farmers who chose "3" at least once, revealing a subset who also selected combinations like "123", "23", or single values. This broader group included 44 farmers for drought and 69 for frost, with 28 overlapping. Their typology was distributed as follows: 15 type 1, 10 type 2, 1 type 3, and 2 uncategorized. Additionally, the Willingness to Accept (WTA) among the 16 overlapping farmers showed an average WTA of 2.5 for drought and 2.56 for frost, with slightly higher averages of 2.58 for drought and 2.65 for frost among the 11 overlapping farmers.

[20]We also conducted the analyses using the original interval values (two, five, and ten years) instead of the assigned numerical values (one, two, and three), and the results remained consistent.

adapt, we calculated the average across all potential adaptation measures for each farmer, individually for both drought and frost conditions (excluding responses that involved giving up their farm or orchard). This average yielded a numerical value between 1 and 3, indicating the individual's overall willingness to adapt. A higher value suggests a greater willingness to adapt, as it indicates a readiness to implement measures even when extreme events occur less frequently. The average WTA to drought among all farmers is 1.56. In comparison, the average WTA for frost is slightly higher, at 1.65.

Figure 27: WTA and Yield Loss



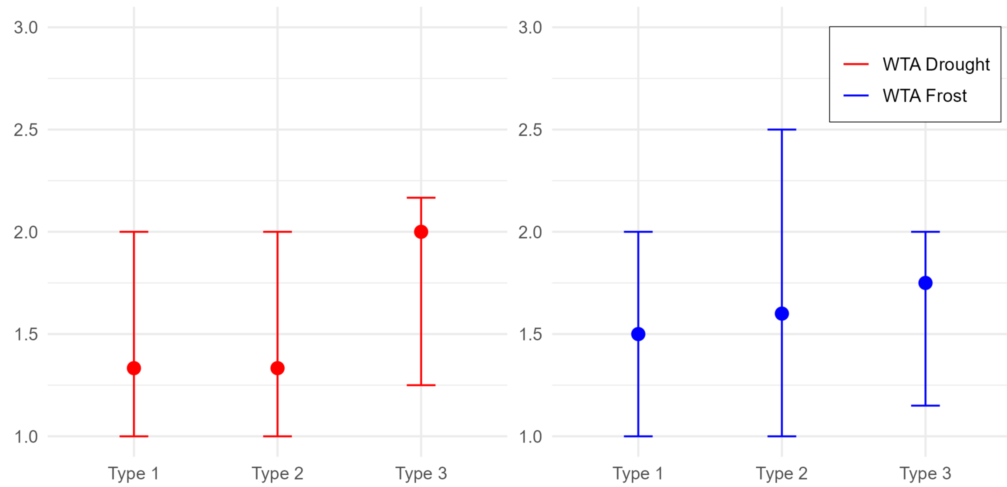
Notes: Farmers willingness to adapt (WTA) to drought or frost, dependent on the specific yield losses caused by drought (left) or frost (right) occurrences, categorized into distinct intervals. The y-axis represents the willingness to adapt, with higher values indicating a greater willingness to adapt.

We can then contextualize the willingness to adapt by examining its relationship with yield loss and the belief typologies. Figure 27 illustrates a trend in individuals' WTA concerning varying levels of losses. Initially, WTA decreases with diminishing losses, followed by an increase at minimal to zero loss levels. Despite this trend, mean WTA values across distinct groups show no statistically significant differences. This trend remains consistent when the sample is limited to full-time farmers (see Figure 35 in the Appendix). One hypothesis is that farmers experiencing high losses exhibit a strong inclination to adapt, driven by necessity, while those with minimal losses retain a sense of adaptability if required. Intermediate loss levels appear to correlate with the lowest willingness to adapt.

When we compare the WTA values across belief typologies (see Figure 28), Type 3 exhibits the highest mean WTA value, indicating greater readiness to adapt. Type 3, characterized by the belief that climate change is not occurring and lacks human influence, demonstrates the highest propensity for adaptation. Conversely, respondents of Type 1 and Type 2 display a lower willingness to adapt to future climate changes despite acknowledging climate change.[21] This observation challenges the intuition and findings of other studies, suggesting that disbelief in climate change correlates with higher adaptation readiness. This phenomenon cannot be explained by differences in irrigation infrastructure, see Figure 32 in the Appendix. A plausible hypothesis is that farmers who believe in climate change may have adopted adaptive measures earlier,

[21]When the sample is restricted to full-time farmers, the effect for drought becomes more pronounced, while the effect for frost is no longer observed (see Figure 36 in the Appendix).

Figure 28: WTA and Belief Type



Notes: Farmers' willingness to adapt (WTA) to drought or frost, dependent on the belief typology. A higher WTA value is an indication of a higher willingness to adapt. The left relates to WTA Drought and the right to WTA Frost.

whereas climate skeptics might have delayed such actions. Interestingly, Type 3 has the highest proportion of fixed irrigation infrastructure; however, fixed irrigation systems are just one of several adaptation measures. One other plausible explanation is that non-believers in climate change may exhibit greater optimism, contrasting with the potential resignation among those who acknowledge climate change. Further research in this area is needed to fully grasp the underlying mechanisms and interplay between farmers' WTA and their climate beliefs.

It is observed that in the case of drought, respondents with fixed irrigation systems demonstrate a higher average WTA than those with either no irrigation or mobile irrigation infrastructure. In contrast, under frost conditions, the average WTA is relatively consistent across all three categories of irrigation infrastructure.

We conducted a regression analysis testing the effect of individual characteristics – such as age, sex, and experience – along with the impact of losses due to drought and frost and the capacity to mitigate these losses on the willingness to adapt. However, the resulting coefficients were not statistically significant and rather small. Additionally, the R-squared values were very low, indicating that the explanatory variables account for only a small portion of the variance in WTA. We conclude that the overall explanatory power of the models is limited, highlighting the complexity of factors influencing individual WTA.

Another survey question assesses the degree of concern among farmers regarding specific climate risks and their potential impacts on agricultural operations. We posit that heightened worry among farmers regarding drought, water scarcity, or frost correlates with an increased willingness to adapt to respective climatic challenges. To investigate this hypothesis, we construct two distinct metrics for drought concern: one focusing solely on worry related to severe drought events, and the other encompassing apprehension towards warmer summer temperatures and heightened occurrences of heat waves. Our analysis shows minimal positive correlations, suggesting almost no linear relationship between farmers' concerns and their willingness to adapt. The level of worry exhibited by farmers appears to have no significant influence on their willingness to adapt.

2.5 Discussion and Conclusions

This paper examines the impacts of frost and drought on perennial crop farmers in Switzerland, addressing a gap in the existing literature related to research on this specific group of farmers. We conducted a nation-wide survey, collecting information on the characteristics of the farm, on both the climate impacts of frost and drought, on the farmer's individual assessment with regard to climate perceptions, expectations, and beliefs, and on their individual characteristics. Additional questions were aimed at their attitudes towards environmental policies and incentive programs, as well as their perceived responsibilities towards the environment. Based on these survey questions we developed three different measures for data analysis. First, we built climate belief typologies, following the approach of Niles and Mueller (2016). Additionally, we created a policy support index, indicating the level of support towards policy measures and governmental incentive programs. Finally, we constructed a willingness to adapt index, a measure of how quickly farmers would respond if extreme climate events were to become more frequent.

Our findings reveal significant average harvest losses exceeding 20 percent due to frost over the last decade, with losses from frost being notably higher than those from drought. However, this does not reflect farmers' future concerns, as more farmers anticipate that their farm operations will be more affected by drought than frost in the future. Interestingly, farmers express a slightly higher willingness to adapt to drought than to frost, which may be influenced by the fact that drought adaptation strategies are more widespread and easier to implement. For instance, irrigation has proven to be a highly effective mechanism against drought. When including other adaptation measures such as soil cultivation, ground cover, shading, and the cultivation of drought-resistant crops, farmers were able to prevent, on average, 20 percent of the losses in 60 percent of cases. While this is substantial, it raises the question of whether further improvements could be made. In contrast, adaptation measures against frost, such as overhead irrigation, heating, and air circulation, have been effective in reducing losses by up to 30 percent in at least a third of instances over the past 10 years.

Exposure to specific climatic shifts influences farmers' perceptions of these events. Our study finds that farmers are more adept at detecting trends in temperature – particularly winter temperature, summer temperature, and heat days – than they are at detecting trends in frost and precipitation. Consistent with existing literature, we also find that farmers with fixed irrigation systems have significantly better recognition of precipitation trends compared to those without such systems or with no irrigation at all. Farmers expect more droughts than frost events in the future, which is in line with climate projections. They also anticipate more intense droughts in the future.

In terms of climate beliefs, the majority of farmers express concerns about climate change, acknowledging an increase in global average temperatures, which aligns with the broader literature. However, fewer farmers agree on the human contribution to climate change. When analyzing different climate belief types, we observe a positive correlation between belonging to Type 1 (belief in climate change and human contribution) and having more accurate climate perceptions. Climate change believers also tend to have a higher policy support index, reflecting greater support for environmental regulations and a higher likelihood of participating in government incentive programs for climate change mitigation and adaptation, as expected. Surprisingly, this does not translate into a greater willingness to adapt. Contrary to expectations and prior research, we find that climate skeptics exhibit a higher willingness to adapt, which cannot be explained by the already implemented infrastructure. Acknowledging climate change does not necessarily lead to adaptive behavior. Climate change believers may experience frustration or disillusionment, which could manifest in resistant behavior. Or this behavior could also be linked to either the specific geographic location where this research was conducted or to the fact, that we analyzed perennial crop farmers. These hypotheses highlight the need for further research to fully understand these complex inter-dependencies. Moreover, our findings suggest that farmers currently prioritize concerns about government regulations over climate impacts, expressing more concern about rising costs and regulatory issues than the effects of frost and drought.

Overall, this study contributes to a deeper understanding of farmers' adaptation mechanisms, perceptions, and beliefs, which are crucial for addressing future climatic changes. The complex process of adaptation in agriculture requires ongoing research, reinforcing the conclusion that there is no one-size-fits-all solution for enhancing agricultural resilience. Effective climate adaptation in agriculture will depend on stakeholder involvement and collaboration among researchers, advisers, and policymakers.

Further research could also explore the implications of these results for aggregate agricultural productivity in Switzerland as climate change intensifies, according to the percentages of farmers believing vs. not believing in climate change.

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Appendix

Figure 29: Cantonal Distribution of Survey Respondents

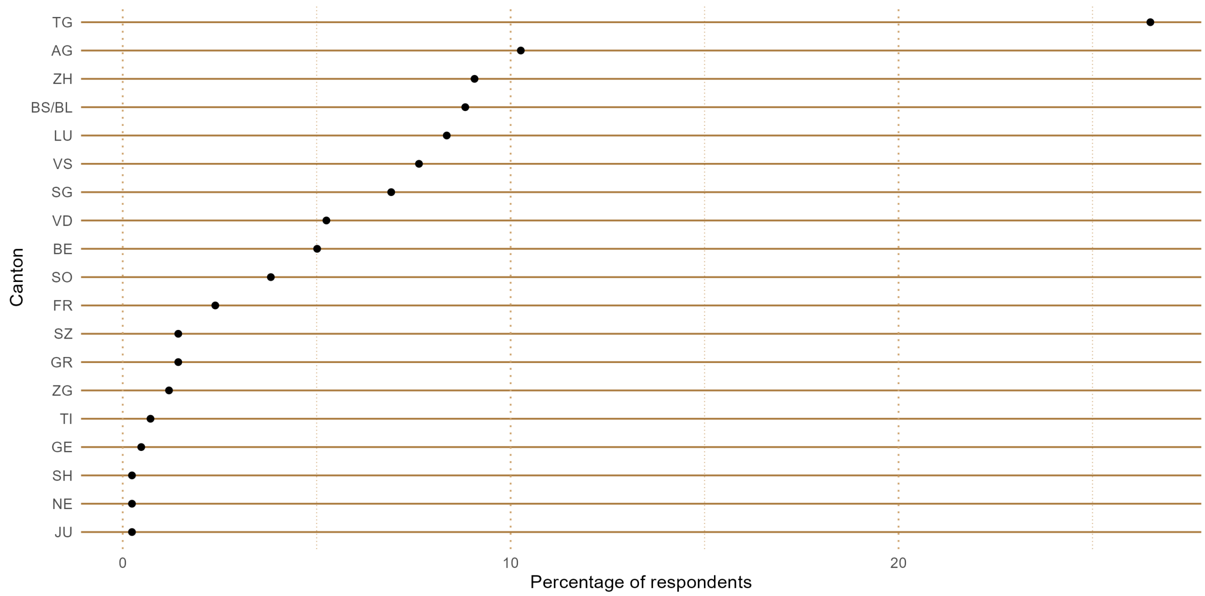
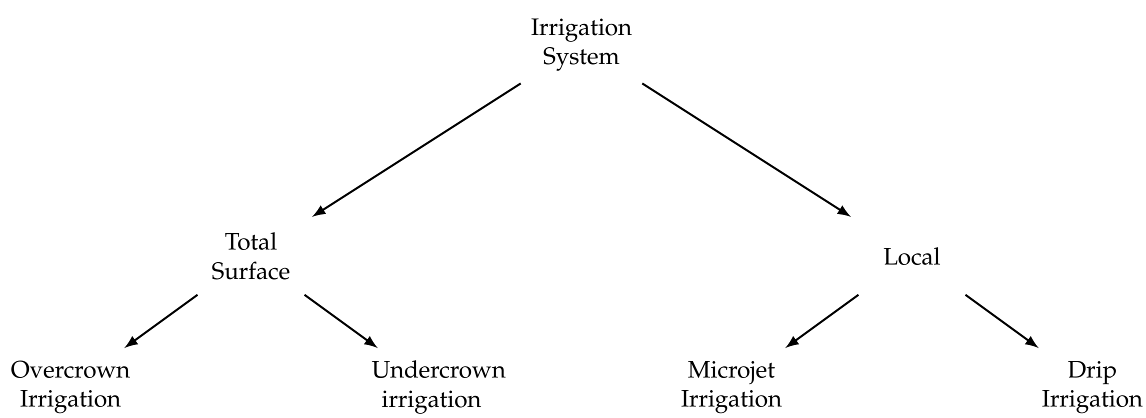
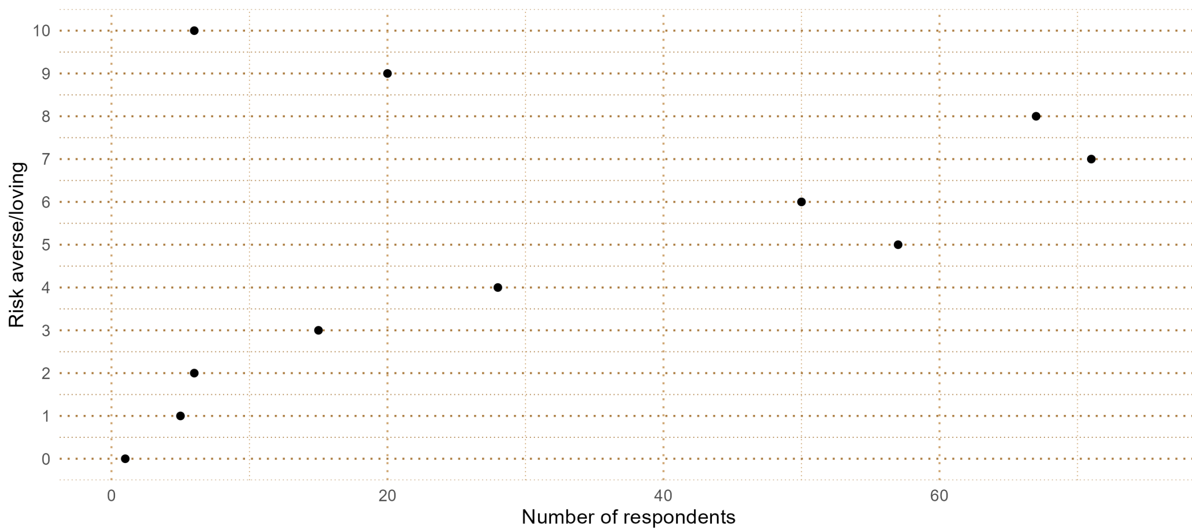


Figure 30: Irrigation Systems



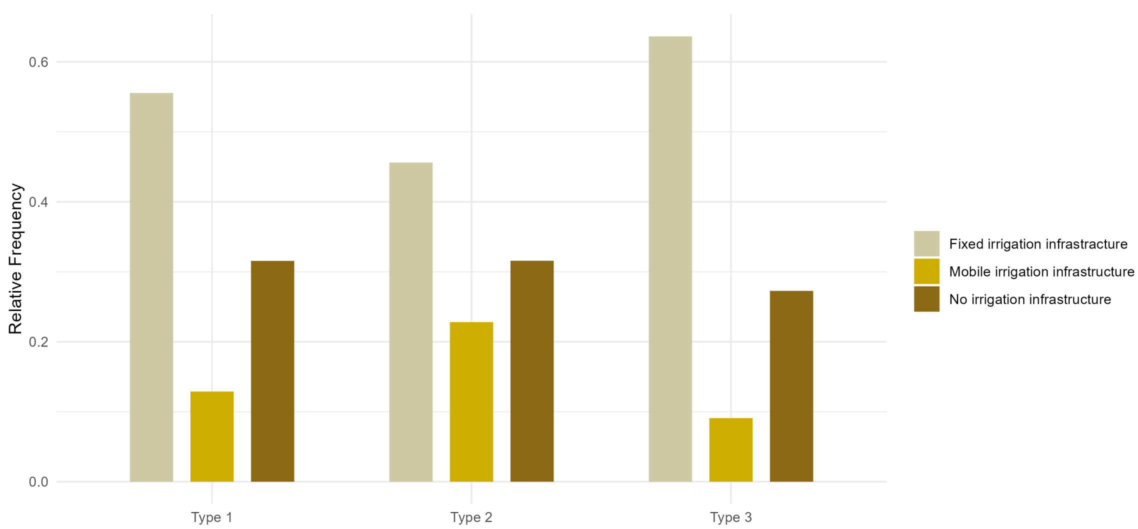
Notes: Overview of different irrigation systems, starting with the differentiation between local or total surface irrigation.

Figure 31: Farmers' Willingness to Take Risks



Notes: Distribution of farmers self-reporting on their willingness to take risks on a scale of zero to ten, where zero means "not at all willing to take risks" and ten means "very willing to take risks". Farmers tend to be more risk taking on average.

Figure 32: Infrastructure and Belief Type



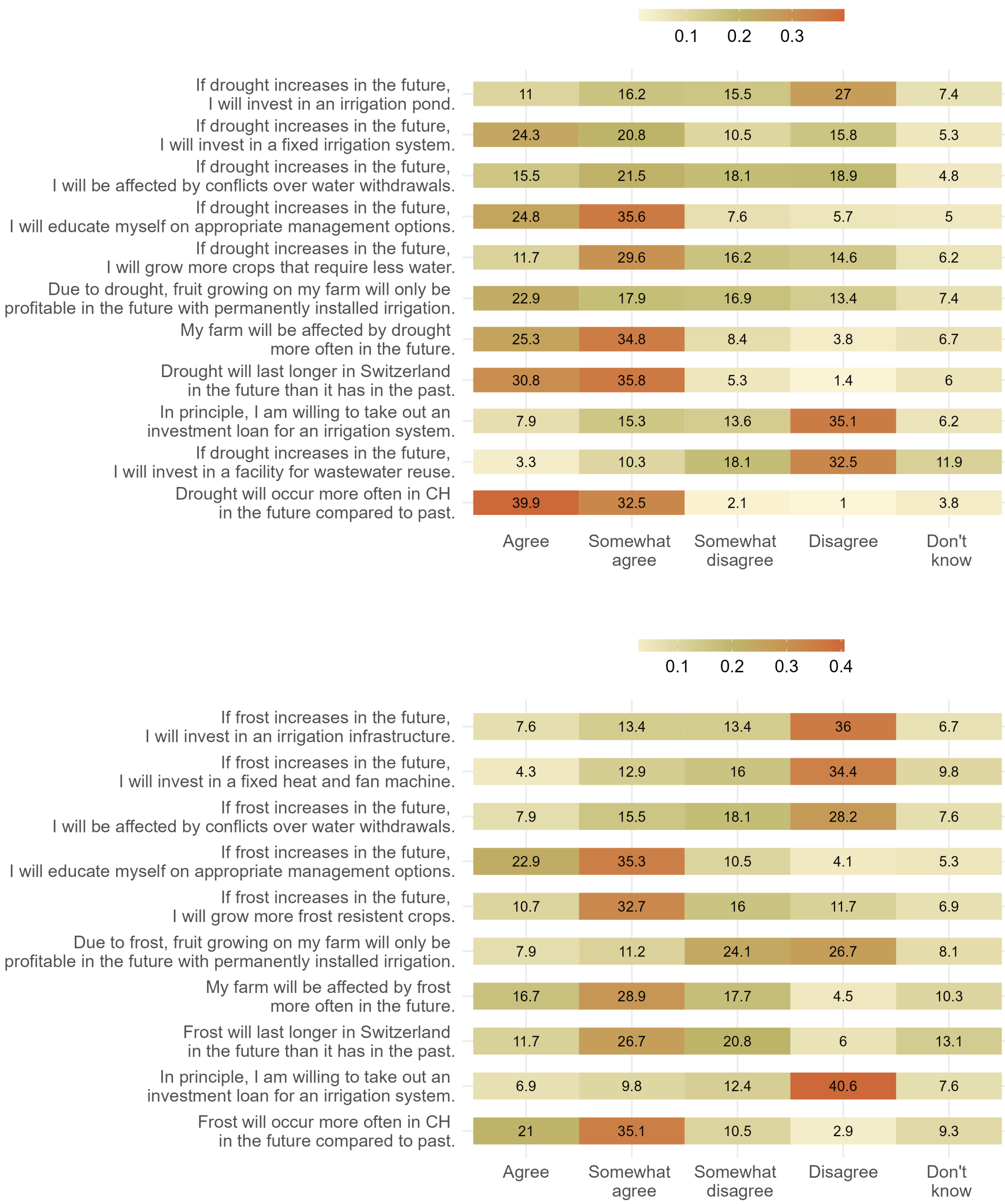
Notes: Distribution of irrigation infrastructure equipment across the three belief typologies shows minimal variation. Type 3 has a slightly higher presence of fixed irrigation infrastructure compared to Type 1 and Type 2, while Type 2 exhibits the highest percentage of mobile irrigation infrastructure.

Table 16: Trends in Climate Variables

Station	Canton	Summertemp	Wintertemp	Temp	Prec	Frost days	Heat Days
BER	BE	0.0452*	0.028	0.0331*	-0.007	0.098	0.1956*
KOP	BE	0.0311*	0.0364*	0.0292*	-0.0135*	0.110	0.172
LAG	BE	0.0258*	0.029	0.0261*	-0.0223*	-0.064	-0.039
WYN	BE	0.0514*	0.0377*	0.0405*	-0.002	0.010	0.2723*
BAS	BL	0.0551*	0.0423*	0.0435*	-0.000	0.000	0.2958*
GVE	GE	0.0500*	0.032	0.0420*	-0.003	-0.1735*	0.217
GLA	GL	0.0496*	0.0383*	0.0418*	-0.001	-0.103	0.1955*
CHU	GR	0.0669*	0.0464*	0.0555*	-0.001	-0.130	0.4094*
GRO	GR	0.020	-0.027	0.003	-0.022	0.1310*	0.5289*
DEM	JU	0.0407*	0.038	0.0345*	-0.0139*	0.012	0.2395*
FAH	JU	0.0508*	0.0437*	0.0443*	-0.010	-0.084	0.1599*
LUZ	LU	0.0463*	0.034	0.0379*	0.006	-0.108	0.2409*
NEU	NE	0.0383*	0.031	0.0343*	-0.004	-0.075	0.1979*
EBK	SG	0.0348*	0.022	0.0256*	-0.017	0.120	0.120
RAG	SG	0.0523*	0.0532*	0.0498*	0.001	-0.140	0.2822*
STG	SG	0.0493*	0.038	0.0400*	0.0137*	-0.084	0.039
HLL	SH	0.0332*	0.0410*	0.0333*	-0.0187*	0.067	0.2000*
SHA	SH	0.0563*	0.0436*	0.0408*	0.005	-0.085	0.2979*
GOE	SO	0.0582*	0.014	0.0269*	0.003	0.177	0.4146*
EIN	SZ	0.0474*	0.033	0.0391*	-0.0223*	-0.061	0.020
GUT	TG	0.0605*	0.0460*	0.0492*	0.000	-0.130	0.2564*
HAI	TG	0.0496*	0.0448*	0.0455*	-0.0113*	-0.2350*	0.065
TAE	TG	0.0518*	0.0441*	0.0424*	-0.001	-0.010	0.1819*
MAG	TI	0.0376*	0.022	0.0343*	-0.012	-0.003	0.4876*
OTL	TI	0.0534*	0.0369*	0.0473*	-0.013	-0.016	0.4399*
ALT	UR	0.0393*	0.0337*	0.0343*	0.001	-0.010	0.098
AIG	VD	0.0469*	0.0364*	0.0400*	-0.008	0.009	0.1791*
CGI	VD	0.0407*	0.029	0.0356*	-0.005	-0.097	0.180
PAY	VD	0.0467*	0.0371*	0.0376*	-0.005	-0.037	0.2664*
PUY	VD	0.0477*	0.033	0.0408*	-0.004	-0.060	0.1868*
SIO	VS	0.0728*	0.0416*	0.0576*	-0.005	-0.1951*	0.6190*
VIS	VS	0.0583*	0.033	0.0464*	-0.002	-0.037	0.4228*
CHZ	ZG	0.0539*	0.003	0.014	-0.008	0.067	0.137
KLO	ZH	0.0476*	0.0407*	0.0397*	0.005	0.134	0.2976*
REH	ZH	0.0525*	0.0454*	0.0444*	-0.002	-0.029	0.2754*
SMA	ZH	0.0482*	0.035	0.0392*	-0.006	-0.028	0.2232*
WAE	ZH	0.0507*	0.0422*	0.0440*	-0.005	-0.118	0.2378*

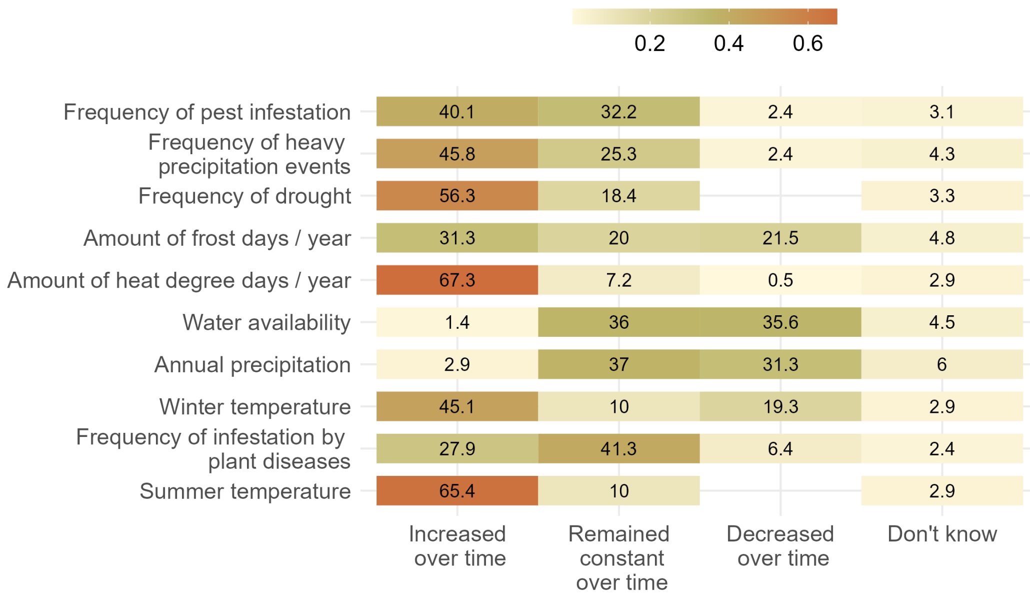
Notes: Linear trends in various climate variables across different weather stations and cantons in Switzerland, calculated through linear regression. The variables include trends in summer temperatures (Summertemp), winter temperatures (Wintertemp), overall average temperature (Temp), precipitation (Prec), frost days (Frost days), and heat degree days (Heat Days). Asterisks ($\star$) next to the values indicate statistically significant trends. The trends reflect changes over time, showing either positive or negative shifts in climate variables at each station.

Figure 33: Farmers' Perspectives on Drought and Frost



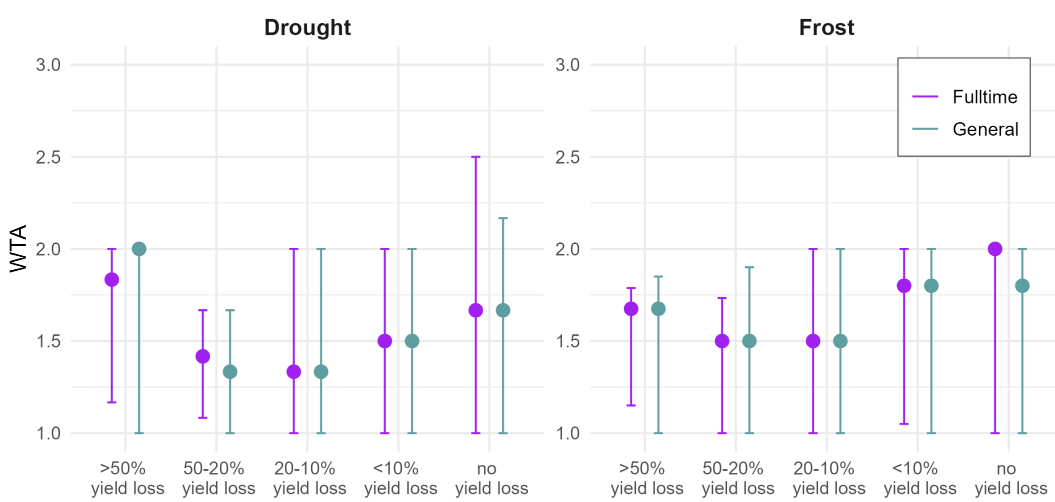
Notes: Farmers' perspectives on the potentially growing occurrence and duration of droughts and frost events, their preparedness for investment in water management and frost protection, and strategies for adaptation and resilience. Farmers Agreement is captured by a Likert scale. The percentage amount of farmers choosing each option is denoted in the color scale on top of the graph.

Figure 34: Perceived Trends in Climate and Environmental Factors



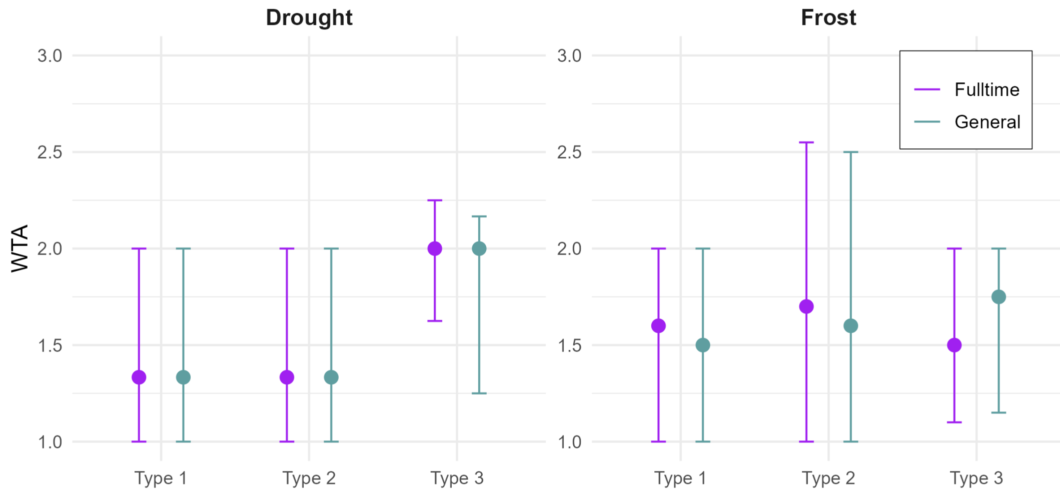
Notes: Farmers' observations on summer and winter temperatures, annual precipitation, water availability, heat and frost days, drought occurrence, heavy rainfall events, and pest and disease incidences in their canton over time. The percentage amount of farmers' answers is denoted in the color scale on top of the graph.

Figure 35: WTA and Yield Loss (Farm Type)



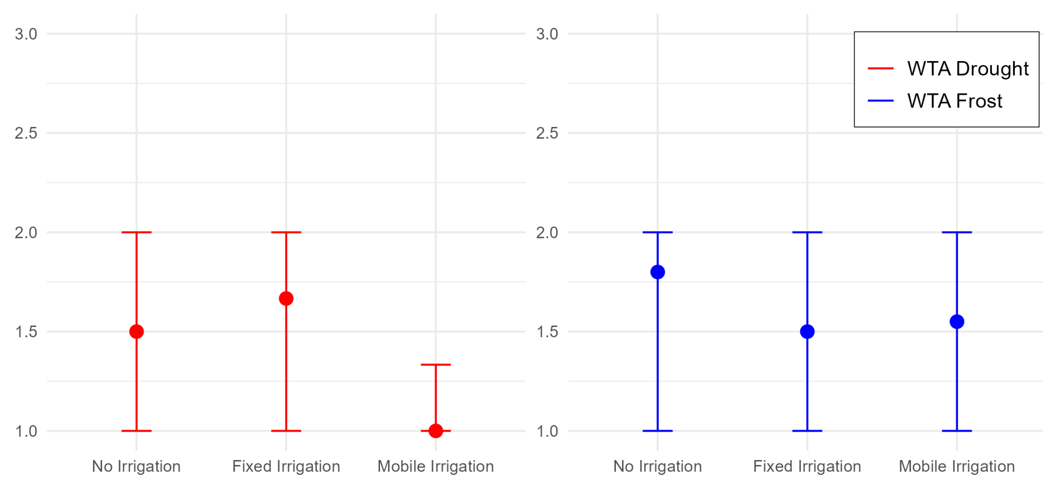
Notes: Farmers' willingness to adapt (WTA) in response to yield losses from drought (left) and frost (right), shown for both the full-time farmer subsample and the combined sample of all farmers.

Figure 36: WTA and Belief Type (Farm Type)



Notes: Farmers' willingness to adapt (WTA) to drought or frost, dependent on the belief typology. A higher WTA value is an indication of a higher willingness to adapt. The left relates to WTA Drought and the right to WTA Frost, shown for both the full-time farmer subsample and the combined sample of all farmers.

Figure 37: WTA and Infrastructure



Notes: Farmers' willingness to adapt (WTA) to drought or frost, dependent on them having a fixed irrigation infrastructure, a mobile one, or no irrigation infrastructure at all. A higher WTA value is an indication of a higher willingness to adapt.

Chapter 3

Strategic Delegation in a Standard Public Goods Game

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Abstract

We provide the first experimental evidence of strategic delegation in the context of public good provision. In a two-stage game, we investigate whether and to what extent two principals delegate the public good choice to agents who hold a different valuation of the public good than their own (strategic delegation). According to theoretical predictions, delegating to an agent with a lower valuation of the public good than the principals themselves is only in their best interest when public good choices are strategic substitutes. To explore this, we conduct two different treatments, one with linear benefits from public good provision (rendering contribution choices dominant strategies) and one with strictly concave benefits (rendering contribution choices strategic substitutes). We find strong evidence for conditional cooperation, i.e., principals delegate to agents with higher benefits from public good provision if they expect the other principal to do the same. However, we observe no significant difference in delegation patterns between the two treatments. This may stem from principals' limited expectations regarding changes in agent behavior relative to the agents' valuation of the public good. Our findings suggest that the "race to the bottom" due to strategic delegation in public good provision may be less severe than predicted by economic theory.

Keywords: strategic delegation, public goods game, lab experiment, conditional cooperation

JEL-codes: D72, P48

3.1 Introduction

The provision of public goods often faces significant challenges due to free-riding incentives, a well-documented issue in economic literature and beyond. Mitigating climate change is a prime example: as each country's contribution will benefit all countries in a non-exclusive and non-rival manner, all countries will provide inefficiently low levels of greenhouse gas (GHG) emission abatement. This example, however, also reveals the complexity of real-world governance: there is no one person who decides on the climate policy of each individual country. Instead, representative democracies operate through a chain of delegation from voters to policymakers (Strøm 2000): (i) from voters to elected representatives, (ii) from legislators to the executive branch (head of government), (iii) from the head of government to the heads of different executive departments, and (iv) from these heads to civil servants. In each step, one party (the agent) acts on behalf of another (the principal). Delegation occurs because the principal may lack the information, skills, or time that the agent possesses. Additionally, selecting an agent with specific preferences can signal the principal's intentions, thus, credibly committing to certain actions (e.g., Ludema and Olofsgård 2008; Tavoni and Winkler 2021). This form of delegation, i.e., delegation as a commitment device, is called *strategic delegation*.

In this paper, we analyze the extent to which principals strategically delegate to agents, who then decide on behalf of the principals on the contributions to a public good. To the best of our knowledge, we are the first to analyze this question in an experimental setting.

The simplest form of a delegated public goods provision game, which we employ in our experimental set-up, involves two principals who are identical with respect to the benefits and costs of public good provision. In the first stage, these principals simultaneously choose one agent from identical pools of available agents who vary in their valuation of the public good and, thus, have different incentives to provide the public good. In the second stage, the two chosen agents simultaneously decide on their contribution to the public good. Under conditions of complete information, i.e., costs and benefits of public good provision of all involved parties are common knowledge, principals can credibly commit to high or low public good provision by selecting an agent with either a high or low valuation of the good.

Delegating to agents who have a different valuation of the public good than the principal themselves typically results in different contribution decisions from what the principal would have otherwise chosen. This can be beneficial, if this changed action triggers a favorable best response from the other principal's agents. More precisely, strictly concave benefits from public good provision render public good contributions strategic substitutes. Put differently, an agent's best response to a decrease in the public good provision by the other agents is to increase its own provision of the public good. Thus, principals commit to lower public good provision by delegating to agents with a lower valuation of the public good than they hold themselves, prompting the other agents to increase their own contributions in response.

This incentive to strategically delegate disappears if public good provisions are dominant strategies, i.e., the best response is independent of the other agent's actions. Accordingly, we conduct two different treatments of a delegated public goods provision game. In the first treatment, benefits from the public good are linear in the total provision of the public good for both principals and agents, thus eliminating any incentive to delegate strategically. In the second treatment, however, benefits from public good provision are strictly concave, rendering the public good provision choices strategic substitutes. Consequently, this treatment creates an incentive for principals to delegate to agents who have a lower valuation of the benefits than they have themselves.[22] Comparing the principals' choices of agents across treatments allows us to isolate the effect of strategic delegation due to the strategic substitutability of public good contributions.

Non-linear public goods games are inherently complex, and more so in the case of an additional delegation stage. Due to the non-linearity, public good contributions are no longer dominant strategies, which requires participants to form beliefs about the other agent's contribution choices. Additionally, calculating payoffs becomes more challenging. The situation is even more intricate for the principals, who not only have to form beliefs about the other principal's choice of agent but also how these choices will influence the agents' public good provisions in the second stage. To facilitate comprehension and belief formation, we embedded an intuitive payoff calculator in the experiment, which allowed subjects to input hypothetical choices for all players and automatically computed the ensuing payoffs for all.[23] To avoid nudging individuals with specific choices, no default option was presented, and subjects needed to pick an initial value before the slider appeared.

Another challenge is implementing the two-stage game in an experimental setting, particularly in an online environment. We leverage the game's sequential structure for a novel implementation protocol. Restricting the choice of agents in the first stage to five potential candidates (significantly lower, lower, same, higher, and significantly higher evaluation of the public good than the principals have themselves) results in a total of 25 different second-stage games. Thus, to derive the information on public good contributions in the second stage, we recruit players who play all potential 25 second-stage games in a random order, without feedback on other players' choices after each game. Since contributions in the second stage are made simultaneously, we do not require both agents to participate simultaneously. Instead, each player completes the sequence of 25 games and is matched to a prior subject for payoff calculation. Once we have gathered sufficient data from the second stage, we run the first stage, in which principals select an agent. Again, every player in the first stage of the experiment is matched to the prior subject to determine the combination of agents who decide on public good contributions. For both principals, a second-stage player is randomly chosen from the second-stage dataset, and the contribution this agent made in the respective second-stage game determines the public good contribution, which is payoff-relevant for the principal. This implementation protocol is particularly suited to online experiments, as it eliminates the need for all four players to be available at the same time.

The experimental literature on public goods games has established that players are motivated by more than just their own payoffs. Specifically, most players can be classified as "conditional cooperators", i.e., they are willing to deviate from the inefficient under-provision Nash equilibrium if they believe that other players will do the same. Consequently, public good experiments find that average contributions are significantly higher than the Nash equilibrium contributions of purely self-interested players, though they still fall short of the level required for efficient public good provision. We observe the same behavior in the second stage of our strategic delegation public goods game. Average contributions are significantly above the levels predicted by the Nash equilibrium when players are solely motivated by their own payoffs. Additionally, agents contribute significantly more when they expect higher contributions from the other agent. As anticipated, this effect is smaller in the quadratic treatment.

[22] As we use a linear benefit function in the first and a concave quadratic benefit function in the second treatment, we consistently refer to the two treatments as the "linear" and "quadratic" treatments.

[23] A screenshot of the game interface, including the payoff calculator, is provided in Figure 40.

Our expectation that conditional cooperation significantly influences the first stage is supported by our findings. We find that principals delegate to agents with a higher valuation of the public good if they believe the other principal will do the same. This is in stark contrast to the theoretical prediction when players only care about their own payoffs: in such cases, delegation to agents with a higher than own valuation of benefits is never in the best interest of principals. However, our hypothesis that conditional cooperation would not entirely override strategic delegation incentives is not supported by the experimental results. Specifically, we observe no significant difference in the choice of agents across our two treatments. While we have to be careful to extrapolate from the very specific set-up of our delegation public goods game to delegation in public goods contexts in general, our results indicate that the "race to the bottom" induced by strategic delegation may be substantially less severe than indicated in the theoretical economic literature.

The remainder of the paper is structured as follows: In Section 3.2 we discuss how our paper contributes to the theoretical and experimental literature on strategic delegation, in particular with respect to public good provision. Then, we briefly explore the incentives for strategic delegation in the simple model framework that also informs our experimental set-up in Section 3.3. In Section 3.4 we introduce our experimental design, state and discuss our hypotheses regarding the results of our experiment, and explain in detail the particular implementation protocol of our experiment. We report the results for the second and first stages of our experiment in Section 3.5. Finally, in Section 3.6 we discuss our results and conclude.

3.2 Related Literature

The theoretical literature on strategic delegation emerged in the Industrial Organization literature analyzing the delegation of managerial decisions from shareholders to chief executive officers (see Kopel and Pezzino 2018). Subsequently, the concept of strategic delegation found its way into the literature on negotiation and cooperation (e.g., Burtraw 1992, 1993; Crawford and Varian 1979; Jones 1989; Segendorff 1998; Sobel 1981), where it has been utilized in various contexts with inter-agent spillovers, such as environmental policy or the provision of public goods more generally.[24]

More related to the provision of public goods, Siqueira (2003), Buchholz et al. (2005), Roelfsema (2007) and Hattori (2010) analyze strategic voting in the context of environmental policy. Siqueira (2003) and Buchholz et al. (2005) both find that voters' selection of agents is biased toward politicians who are less green than the median voter. By electing a more "conservative" politician, the home country commits itself to a lower tax on pollution, shifting the burden of a cleaner environment to the foreign country. By contrast, Roelfsema (2007) accounts for emissions leakage through shifts in production and finds that median voters may delegate to politicians who place greater weight on environmental damage than they do themselves, whenever their preferences for the environment relative to their valuation of firms' profits are sufficiently strong. However, this result breaks down in the case of perfect pollution spillovers, such as the emission and diffusion of greenhouse gases. Hattori (2010) allows for different degrees of product differentiation and alternative modes of competition, i.e., competition on quantities but also on prices. His general finding is that when the policy choices are strategic substitutes (complements), a less (more) green policymaker is elected in the non-cooperative equilibrium.

[24] Strategic delegation is often called "strategic voting" when the principal is the electorate or, more precisely, the median voter and the elected government is the agent (e.g., Persson and Tabellini 1992).

Strategic delegation in the provision of public goods with cross-border externalities more generally has been examined by Kempf and Rossignol (2013) and Loeper (2017). The authors of the former paper show that any international agreement that is negotiated by national delegates involves higher public good provisions than in the case of non-cooperative policies, taking feasibility, efficiency, and equity constraints into account. In their model, the choice of delegates is highly dependent on the distributive characteristics of the proposed agreement. Loeper (2017) proves that whether cooperation between national delegates is beneficial only depends on the type of public good considered and, more specifically, on the curvature of the demand for the public good but not on voters' preferences, the magnitude of the cross-border externalities, nor the size, bargaining power or efficiency of each country in providing the public good.

There is extensive experimental economic literature on linear public goods games.[25] The early literature till the mid-1990s found two main results: (i) In one-shot public goods games, participants contributed on average approximately half their endowment to the public good, which is halfway between the socially optimal contribution and the non-cooperative Nash equilibrium contribution predicted by non-cooperative game theory. However, individual contributions covered the full range from 0% to 100%. (ii) In environments, where the one-shot public goods game was played repeatedly, average contributions to the public good started at approximately 50% (as in the one-shot game) and declined with increasing number of repetitions.[26]

To explain the deviations from theoretical predictions, different behavioral theories have been proposed: Fehr and Schmidt (1999) and Bolton and Ockenfels (2000) focus on agents' inequity aversion. According to these theories, agents contribute more if others also contribute more due to their concerns for equity in pay-offs. Building on Rabin (1993), Dufwenberg and Kirchsteiger (2004) and Falk and Fischbacher (2006) show that explicitly incorporating the players' beliefs about other players' strategies together with reciprocal motivations, public goods games can turn from a prisoner's dilemma game to a coordination game, in which both the non-cooperative Nash equilibrium and the social optimum, together with other outcomes in between, constitute stable equilibria. Both strands of literature allow for conditional cooperation. Sonnemans et al. (1999), Fischbacher et al. (2001), Keser and van Winden (2000), among others, report experimental evidence for such tendency in public goods games. In an effort to test the robustness of conditional cooperation behavior, Burlando and Guala (2005), Fischbacher and Gächter (2010) and Kurzban and Houser (2005) consistently find that players can be classified into three different groups: (i) unconditional cooperators, (ii) conditional cooperators and (iii) free-riders. While the shares of these groups vary with experimental design, the group of conditional cooperators usually has the highest share. These findings are robust to variations in the cultural and educational characteristics of participants (e.g., Brandts et al. 2004; Hermann and Thöni 2008; Kocher et al. 2008).

An important question with respect to our paper is whether and to what extent delegation can foster public goods provision *within* and *across* groups. In fact, the experimental literature on delegation and public goods provision is surprisingly sparse.[27] Several studies report that the free-riding incentives in public

[25] In linear public goods games, n players simultaneously split a given endowment between a private and a public account. Players' pay-offs are their private accounts plus the total sum over all players to the public account multiplied by some fraction α (marginal per capita return) with $0 < \alpha < 1 < n\alpha$. Under these circumstances, non-cooperative game theory predicts that, if players only care about their own pay-offs, all players assign the full endowment to the private account, while the Pareto dominating social optimum would be that all players allocate their full endowment to the public account.

[26] See Ledyard (1995) and Chaudhuri (2011) for authoritative surveys on linear public goods experiments.

[27] There exists also a small literature testing strategic delegation in other experimental contexts, such as the ultimatum game (e.g., Fershtman and Gneezy 2001; Choy et al. 2016), the dictator game (e.g., Hamman et al. 2010; Bartling and Fischbacher 2012) and bargaining (e.g., Schotter et al. 2000).

goods provision *within groups* can at least be alleviated by different institutions of delegation. For example, Güth et al. (2007) find that "leading by example", i.e., one player appointed as a leader (either by election or randomly assigned) first contributes, then all other players, after observing the leader's contribution, decide about their own contribution, significantly increases public goods provisions. However, this leading-by-example effect is drastically reduced if players' endowments are heterogeneous across players or private information (Levati et al. 2007). Another institutional design for leadership is that leaders make non-binding contribution suggestions to players prior to the players' contribution choices. Levy et al. (2011) show that leaders' contribution suggestions indeed have a significant effect on players' contributions. They find that leader suggestions act as an upper bound to the player's contribution schedules. While, on average, leadership has a positive effect on public goods provision, it is detrimental in cases where leaders suggest low contributions. Kroll et al. (2007) investigate whether a non-binding vote on the provision of a public good prior to the contribution stage can increase public goods provision. They find that voting alone does not yield substantially higher public goods contributions. If, however, voting is combined with a costly punishing mechanism, in which players who deviate from the majority proposal can be punished, significantly decreases free-riding incentives.

Another strand of literature studies institutions in which leaders have more formal power over the other players' contributions. Oxoby (2013) investigates a one-shot public goods game in which players can either directly mandate the contributions of others or at least limit their feasible choice set. He finds that dictated contribution levels are significantly higher and even approximate socially efficient levels. Interestingly, if players can dictate different contribution levels for themselves and all other players, almost 70% of players manage to resist the temptation to free-ride on the mandated contributions of the others. Bolle and Vogel (2011), however, report that this altruistic behavior deteriorates over time in repeated public goods provision games. In addition, players voluntarily submit to an institution in which one leader dictates the contributions of all group members (Fleiß and Palan 2013; Hamman et al. 2011).[28]

To the best of our knowledge, the only paper analyzing delegation in a linear public goods game *across groups* is Kocher et al. (2018). In their set-up, nine players are divided into three groups consisting of three players each. Each group elects a group leader who mandates contributions to the public good for all members of their group. Public good provision, however, depends on the contributions of all nine players across all three groups. This setup is most closely related to the theoretical literature on strategic delegation and public goods provision. However, due to the linear public goods technology, there are no incentives to strategically delegate to exploit the strategic substitutability of public goods provision choices. In line with similar experiments of delegation *within groups* the authors find that (i) delegation increased public good provision compared to the case of non-delegation,[29] (ii) delegates mainly refrain from exploiting their group members, and (iii) contributions within groups decline over time, although slower than in the case of non-delegation. Two further related papers are İriş et al. (2019, 2022). They also feature experiments on hierarchical decision-making, respectively to study the provision of a threshold and standard public good. Both find a negative effect of delegation in terms of reduced contributions with respect to the traditional case of self-representing individuals choosing independently how much to invest in the public good.

[28] Another possible delegation institution is to delegate punishment. Andreoni and Gee (2012) find that a "hired gun" that exhibits a non-exclusive power to punish often results in full compliance in which no punishment is exerted. In addition, punishment – in case it is exerted – is relatively small and, therefore, cost-effective.

[29] However, this effect is exclusively due to alleviating the common action problem *within* each group, free-riding incentives *across* groups remain.

All the aforementioned experimental literature has in common is that it restricts attention to linear public goods games.[30] As already hinted at in the introduction and formally shown in the next section, there is no incentive to strategically delegate in the case of a linear public goods technology; public good contributions are dominant strategies. Thus, our paper is the first to analyze strategic delegation in the case of non-linear benefits from public goods provision.

3.3 Strategic Delegation in the Provision of Public Goods

In the following, we analyze how agents behave with respect to contributing to a public good if each of them can delegate the decision on the public good contribution to another agent. More precisely, we consider a two-stage principal-agent framework in which two principals select agents, which in turn then decide on the provision of a public good.

3.3.1 Timing and Information Structure

In the first stage, each of the two principals simultaneously chooses an agent to whom they delegate the decision on the public good provision. Principals can choose from a set of agents, which differ with respect to the benefits they obtain from the provision of the public good. In the second stage, the delegated agents decide simultaneously and non-cooperatively on behalf of the principal about the public good provision.

Thus, the timing of the game can be summarized as follows:

1. Delegation Stage:
   Principals simultaneously and non-cooperatively choose agents.
2. Public Good Provision Stage:
   Agents simultaneously and non-cooperatively decide on public good contributions x_i.

The payoff functions of all principals and agents are common knowledge. In particular, this implies that principals in the first stage know the payoff functions of the other principal before they choose an agent, and agents in the second stage know the payoff of the other agent before they decide on public good contributions.[31]

[30]There exists a small literature analyzing public goods provision games with smooth non-linear public good technologies. They employ either a concave or convex public goods technology, implying that public goods provision choices are either strategic substitutes or complements. Results consistently show that public goods provision is (i) higher than predicted by theory (like in the linear public goods games) and (ii) significantly higher in case of strategic complementarity compared to strategic substitutability (e.g., Potters and Suetens 2009; Lappalainen 2018).

[31]Note that while the *monetary* payoffs are indeed common knowledge also in our experimental setting, the game theoretical payoff functions of principals and agents, i.e., their preferences, do not necessarily coincide with their monetary payoffs. We shall further discuss this issue in Section 3.4.2.

3.3.2 *Payoffs*

Payoffs decrease with individual contributions x_i ($i = 1, 2$) to the public good and increase with the benefits of total provision $x = x_1 + x_2$. Principals are identical with respect to their payoff functions Π_i ($i = 1, 2$):

$$\Pi_i = B(x) - C(x_i) , \qquad i = 1, 2 . \tag{1}$$

We assume that the benefit function $B(x)$ is strictly increasing and concave, i.e., $B' > 0$, $B'' \leq 0$, and the cost function is strictly increasing and strictly convex, i.e., $C' > 0$, $C'' > 0$.

In the first stage of the game, each principal can choose from a set of agents j. The agents' payoffs π_i^j differ with respect to the benefits of the public good in the following way:

$$\pi_i^j = \theta_i^j B(x) - C(x_i) , \qquad i = 1, 2 , \tag{2}$$

where θ_i^j is a parameter that identifies agent j's type and scales their benefits from public good provision relative to the benefits of their principal i. We assume that $\theta_i^j \in [\theta_{min}, \theta_{max}]$ with $\theta_{min} < 1 < \theta_{max}$. Thus, both principals are able to choose an agent that benefits less, equally, or more from public good provision than they do themselves.

3.3.3 *Strategic Delegation*

In the following, we illustrate how and when principals have an incentive to delegate strategically, i.e., they delegate public good provision to agents who have a different payoff from public good provision than they have themselves, which in our model framework amounts to $\theta_i^j \neq 1$. To this end, we assume that all principals and agents make decisions such as to maximize their own payoffs and characterize the subgame perfect Nash equilibrium of the game by backward induction.

In Stage 2, agents have already been chosen by the principals in the first stage. In addition, the agents' payoffs are common knowledge. As agents only differ in their payoff parameter θ_i^j, principals in the first stage de facto decide on a payoff parameter. Thus, we denote the outcome of the first stage by $\Theta = (\theta_1, \theta_2)$, where θ_i ($i = 1, 2$) is the payoff parameter chosen by principal i.

Then, agents in the second stage choose individual contributions x_i to maximize

$$\max_{x_i} \theta_i B(x_i + x_{-i}) - C(x_i) , \qquad i = 1, 2 . \tag{3}$$

given x_{-i}, where x_{-i} is the public good contributions of the other agent, i.e., $i, -i \in \{1, 2\}$ and $-i \neq i$. As the maximization problems 3 are strictly concave, there exists a unique best response of agent i for any given contributions x_{-i} of the other agent, which is implicitly given by the first-order condition:

$$\theta_i B'(x_i + x_{-i}) = C'(x_i) , \qquad i = 1, 2 . \tag{4}$$

The Nash equilibrium of the second stage is the simultaneous solution of Equations (4) for both agents $i = 1, 2$. It is well known (and shown in Appendix A.0.1) that there exists a unique Nash equilibrium of this second stage. We denote the total and individual public good contributions of this unique Nash equilibrium of the second stage by $x(\Theta)$ and $x_i(\Theta)$ ($i = 1, 2$). Note that public good provision choices are either strategic substitutes ($B'' < 0$) or dominant strategies ($B'' = 0$).

In addition, we investigate how individual and total public good provision choices in the Nash equilibrium of the second stage depend on the payoff parameters θ_i (see Appendix A.0.1):

$$\frac{dx_i(\Theta)}{d\theta_i} > 0\,, \quad \frac{dx_{-i}(\Theta)}{d\theta_i} \leq 0\,, \quad \frac{dx(\Theta)}{d\theta_i} > 0\,, \qquad i = 1, 2\,.$$

We find that an increase in θ_i increases the public good provision of agent i and in total. However, it also decreases the public good provision of agent $-i$ in case of a strictly concave benefit function $B(x)$, or does not affect it if $B(x)$ is linear.

Assuming that principals anticipate the Nash equilibrium outcome of the second stage, i.e., $x_i(\Theta)$ and $x(\Theta)$, when deciding on the agent to which they delegate public good provision, principal i's first stage optimization problem is given by:

$$\max_{\theta_i} B\big(x(\Theta)\big) - C\big(x_i(\Theta)\big)\,, \qquad i = 1, 2\,. \tag{5}$$

for a given θ_{-i} of the other principal.

Taking the first-order conditions (4) of the second stage into account, we can write the principals' first-order conditions in the following way:

$$(1-\theta_i)B'\big(x(\Theta)\big)\frac{dx(\Theta)}{d\theta_i} = -C'\big(x_i(\Theta)\big)\frac{dx_{-i}(\Theta)}{d\theta_i}\,, \qquad i = 1, 2\,. \tag{6}$$

Note that the right-hand side of equation (6) is either positive (if $dx_{-i}/d\theta_i < 0$) or equal to zero (if $dx_{-i}/d\theta_i = 0$). As a consequence, also the left-hand side has to be positive or equal to zero, which implies that $\theta_i \leq 1$.

The intuition for this result is straightforward. The left-hand side denotes the principal's costs of delegating to an agent who values the public good less than they do, i.e., $\theta < 1$, which is given by the payoff loss resulting from the fact that a lower θ_i leads to a lower total provision of the public good. The right-hand side captures the benefits from strategic delegation, which accrue because the public good provision of all other agents increases in equilibrium with a decrease in θ_i. Thus, the incentive for strategic delegation stems from the fact that the principals can free-ride on the public good provision of all other agents due to its strategic substitutability by delegating to an agent with a lower valuation for the public good. In case public good provision choices are dominant strategies, this incentive vanishes, and principals delegate to agents with $\theta_i = 1$.

At least for the functional forms we employ in the experiment (i.e., quadratic or linear benefit function and quadratic cost function), there exists a unique Nash equilibrium of the two-stage game (see Appendix A.0.2). In addition, also the principals' choices of the payoff parameters θ_i are either strategic substitutes (in case of a strictly concave benefit function) or dominant strategies (if the benefit function is linear).

3.4 A Symmetric Strategic Delegation Public Goods Experiment

Our theoretical analysis of the subgame perfect Nash equilibria in the previous section showed that principals have an incentive to delegate to agents who benefit less than they do themselves if the benefit function is strictly concave, while they choose agents who exhibit the same benefits as themselves in case of a linear benefit function.

The reason is that in the case of strictly concave benefits, public good provision choices in the second stage are strategic substitutes (while they are dominant strategies in the case of linear benefits). This means that an agent's best response to a – ceteris paribus – lower provision of the public good by the other agent is to increase the own provision of the public good. Anticipating this incentive in the second stage, principals can – again, ceteris paribus – induce higher public good provision of the other principal's agent by choosing an agent that benefits less from the public good and, hence, also provides less of it in equilibrium. Obviously, this incentive is absent in the case of linear benefit functions, as public good provision choices are dominant strategies, i.e., they are independent of the choice of the other agent.

However, as this incentive to free-ride on the public good provision of the other party by strategically delegating to an agent with lower benefits from the public good provision is mutual, the subgame perfect Nash equilibrium is a two-stage Prisoners' Dilemma: on top of the Prisoners' Dilemma in the second stage, which is due to the positive externality from public good provision, we also have a Prisoners' Dilemma in the first stage in the sense that both principals would be better off if they chose agents that exhibit the same preferences as they hold themselves (self-representation), but self-representation is not a Nash equilibrium (due to the free-riding incentives discussed above).

3.4.1 Experimental Design

In our experiment, we test whether and to what extent we can replicate the results of our theoretical considerations in Section 3.3. In particular, we are interested in whether the principals delegate more strategically if the benefit function is strictly concave instead of linear. As a consequence, we run two sets of experiments (treatments). In the first treatment, the benefit function $B(x)$ is linear, while it is quadratic and, thus, strictly concave in the second treatment. As a consequence, we shall often refer to the two treatments as the "linear" and the "quadratic" treatment.

More precisely, we employ the following functional forms for the benefit function:

$$B_i^l(x) = b_i x \, , \qquad B_i^c(x) = b_i \left(\bar{x} - \frac{1}{2} x \right) \, , \qquad i = 1, 2 \, . \tag{7}$$

where $b_i > 0$ are the so called "benefit parameters". The benefit parameters are set to $b_i = 8$ for the principals in both treatments. Principals can delegate to agents that differ in their benefit parameters. In both treatments, principals have the choice between five agents with benefit parameters $b_i \in \{4, 6, 8, 10, 12\}$.[32] Thus, principals can delegate to agents who have either a lower, the same, or a higher benefit from public good provision than they have themselves. $\bar{x} > 0$ is the "bliss point" in public good provision in the case of our quadratic and strictly concave benefit function $B_i^c(x)$.[33] We set $\bar{x} = 1.89$, which implies that public

[32] Benefit parameters $b_i \in \{4, 6, 8, 10, 12\}$ correspond to the payoff parameters $\theta_i \in \{0.5, 0.75, 1, 1.25, 1.5\}$ introduced in Section 3.3.

[33] As $B_i^c(x)$ is a concave quadratic function, $B_i^c(x)$ is increasing for public good provision levels $0 < x < \bar{x}$ and decreasing for levels $x > \bar{x}$.

good provision in the Nash equilibrium of the second stage of the game is equal to $x_i = 0.44$ in both treatments given that all agents have a benefit parameter of $b_i = 8$ and agents only care about own payoffs. This renders public good provisions across treatments as comparable as possible.

The cost of public good provision is the same for all principals and agents across both treatments and given by:

$$C(x_i) = cx_i^2 \,, \qquad i = 1, 2 \,. \tag{8}$$

with some positive constant $c > 0$, which we set to $c = 9$.

For these functional forms, we obtain in the subgame perfect Nash equilibria, as discussed in Section 3.3, the following equilibrium outcomes. In the case of the linear treatment, both principals delegate to agents with benefit parameters $b_i = 8$, i.e., they delegate to agents that exhibit the same benefits from public good provision as they have themselves. Both agents in the second stage choose public good provisions of $x_i = 0.44$. In the quadratic treatment, both principals delegate to agents with benefit parameters $b_i = 6$, i.e., they delegate to agents that exhibit lower benefits from public good provision than they have themselves. Both agents in the second stage choose public good provisions of $x_i = 0.38$.

3.4.2 Hypotheses

Our theoretical predictions in Section 3.3 rest on the assumption that both principals and agents are only motivated by their own payoffs. However, empirical evidence in the context of public goods games suggests that most players can be classified as so-called "conditional cooperators", i.e., players contribute more than suggested by their own payoff maximization if they observe or believe that other players contribute more, too (e.g., Burlando and Guala 2005, Fischbacher et al. (2001), Fischbacher and Gächter 2010, Keser and van Winden 2000, Kurzban and Houser 2005 and Sonnemans et al. 1999).

Conditional cooperation in the case of our delegation public goods game has two different implications: In the second stage, which resembles a standard one-shot public goods game, conditional cooperation implies that agents contribute more to the public good as suggested by their own payoff maximization if they believe that the other agent also contributes more. Note that for the quadratic treatment, this is in stark contrast to the expected behavior if players maximize their own payoff: due to the strategic substitutability of public good provision choices, a player would contribute the less, the higher the expected contribution of the other player.

In the first stage, conditional cooperation implies that they delegate to an agent with higher benefits from public good provision than suggested by their own payoff maximization Nash equilibrium if they expect the other principal to also delegate to an agent with higher benefits. The reasoning is that delegating to an agent with higher benefits of public good provision results – ceteris paribus – in higher public good outcomes, as agents with higher benefits of public good provision contribute – ceteris paribus – more to the public good, independently of whether they are motivated by own payoffs only or are conditional collaborators.

Unconditional Choices

We hypothesize that despite conditional cooperation free-riding incentives with respect to the principals' choices of agents in the first stage cannot be fully overcome (analogously to public good provision in the standard public goods game). This is the underlying reasoning for our first hypothesis:

Hypothesis 1 (Strategic Delegation beats Conditional Cooperation).
Principals delegate more often to agents who have ...

(H1a) ... the same payoff from the public good as they have themselves in the linear treatment.

(H1b) ... a lower payoff from the public good as they have themselves in the quadratic treatment.

Thus, we conjecture that the Prisoners' dilemma situation of the first stage with respect to the selection of agents is robust to conditional cooperation.

Conditional Choices

According to our analysis in Section 3.3, principals never have an incentive to delegate to agents who benefit more from the public good than they do themselves if they are solely motivated by their own payoffs. However, this may not hold true if players are conditional cooperators. In this case, principals might delegate to agents who have a higher benefit from the public good than they have themselves if they expect the other principal to do the same in order to increase public good provision above the inefficiently low provision in the subgame perfect Nash equilibrium. As conditional cooperation is dependent on the expectation of players about other players' actions, we also elicit in our experiment the principals' expectations about the other principal's choice of agent and about the agents' public good contributions. Figure 38 shows the best-response functions in the case of linear and quadratic benefit functions depending on whether players are mostly motivated by their own payoffs or whether they are conditional cooperators. This leads to the following two hypotheses.

Hypothesis 2 (Best Responses when Delegating to Low Benefit Agents).
If principals expect the other principal to delegate to an agent with an equal or lower payoff from the public good than they have themselves, principals delegate more often to agents who have ...

(H2a) ... the same payoff from the public good as they have themselves in the linear treatment.

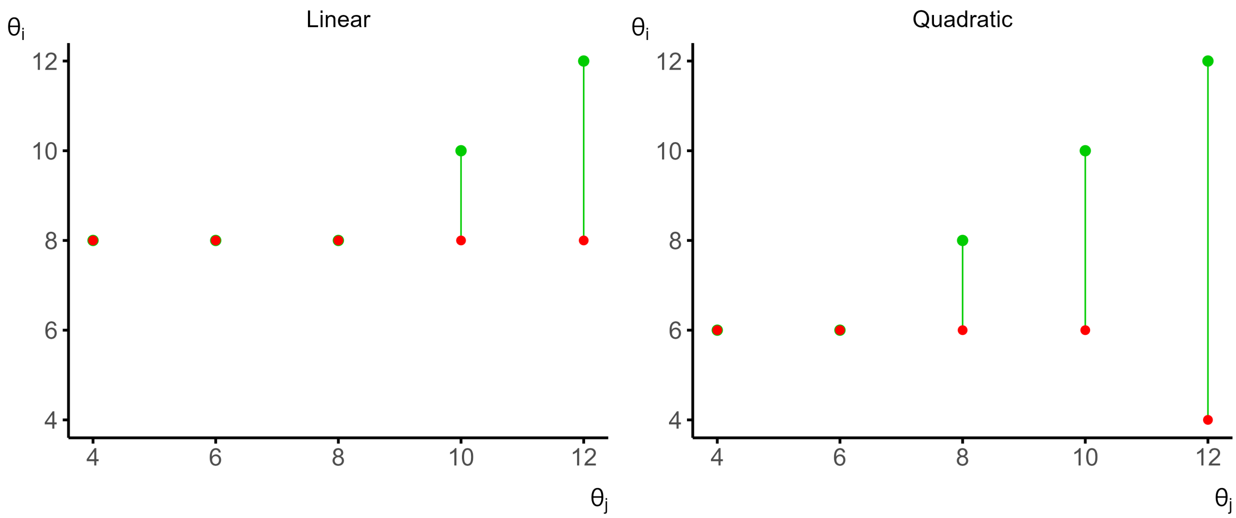
(H2b) ... a lower payoff from the public good as they have themselves in the quadratic treatment.

Hypothesis 3 (Best Responses when Delegating to High Benefit Agents).
If principals expect the other principal to delegate to an agent with a higher payoff from the public good than they have themselves, principals delegate more often to agents who have ...

(H3a) ... either the same or a higher payoff from the public good as they have themselves in the linear treatment.

(H3b) ... lower, the same or higher payoff from the public good as they have themselves in the quadratic treatment.

Figure 38: Best Responses



Notes: Best responses θ_i contingent on the other principal's choice θ_j in the linear (left) and quadratic (right) treatment depending on whether principal i only cares about own payoffs (red) or is a conditional cooperator (green).

As mentioned before, we elicit the principals' expectations of their and the other principals' agents' public good provision. Higher benefits from public good provision increase the agents' incentives to contribute to the public good, irrespective of whether agents are only motivated by their own payoffs or whether they are conditional cooperators. This reasoning leads to the final hypothesis.

Hypothesis 4 (Correct Anticipation of Agents' Public Good Provisions).
Principals expect higher public good contributions in both treatments . . .

(H4a) . . . from their own agent if they delegate to agents with higher payoffs from the public good.

(H4b) . . . from the other principal's agent if they expect the other principal to delegate to an agent with higher payoffs from the public good.

3.4.3 Implementation

The typical lab setup to conduct a two-stage delegation public goods game involves inviting participants in multiples of four, grouping them, and randomly assigning roles. Principals then select benefit functions for their agents, who must wait until these choices are made before deciding on public good contributions. While straightforward, this approach incurs considerable overhead cost and time. Labs must overbook sessions to account for no-shows, often paying show-up fees to dismissed participants. The sequential decision process creates waiting times, as principals and agents await each other's choices yet require compensation. Limited lab capacity – typically 40 participants or ten groups per session – means obtaining 100 observations per treatment would require at least 20 sessions or more for smaller labs.

Our experiment consists of two simultaneous one-shot games, i.e., in which both the principals in Stage 1 and the agents in Stage 2 make decisions without knowing the decision of the respective player. As a result, these decisions can be collected consecutively rather than requiring simultaneous, in-lab interactions.

By departing from the traditional lab approach, this novel method effectively mitigates the majority of standard setup inefficiencies.

Second Stage

Our implementation strategy can be best described as "backward implementation", i.e., we first gather data on the second stage of the game. Principals have a limited choice set in the first stage. Each of them can choose between five different benefit parameters for the benefit function of the agent. This gives rise to a total of 25 different second-stage games. We let agents play all 25 possible second-stage one-shot games.[34] For each agent, this generates a complete set of 25 public good contribution decisions, covering all possible scenarios that could result from principals' delegation choices. To be more precise, participants in both treatments of the second stage first get detailed instructions on gameplay. They are informed that they will participate in 25 rounds of one-shot public goods games with another agent, with varying benefits from the public good for themselves and the other agent in each round. After a brief tutorial to introduce the game interface, participants proceed to the actual game; agents who fail the tutorial five times are removed from the game. Participants then play all 25 possible combinations of benefit parameters in a random sequence. In each round, they are shown their own and the other agent's benefit function and are asked to choose a public good contribution between 0% and 100% in 1% increments. Additionally, we ask them about their expectation regarding the other agent's contribution. To simplify payoff calculations for participants, we provide them with a payoff calculator, in which they can set any combination of their own and the other agent's public good contribution and directly view their resulting payoff for both agents, along with the total sum of payoffs (see Figure 39).[35]

Players complete all 25 rounds without receiving feedback on the decisions of the other agent. We include two attention checks after Round 8 and Round 16 to keep the player attentive over the 25 rounds. Agents are removed from the game if they fail the attention checks five times. After completing the game, players fill out a questionnaire that collects information such as age, gender, education level, degree of mathematical literacy, as well as their attitudes toward trust, risk, and donations.

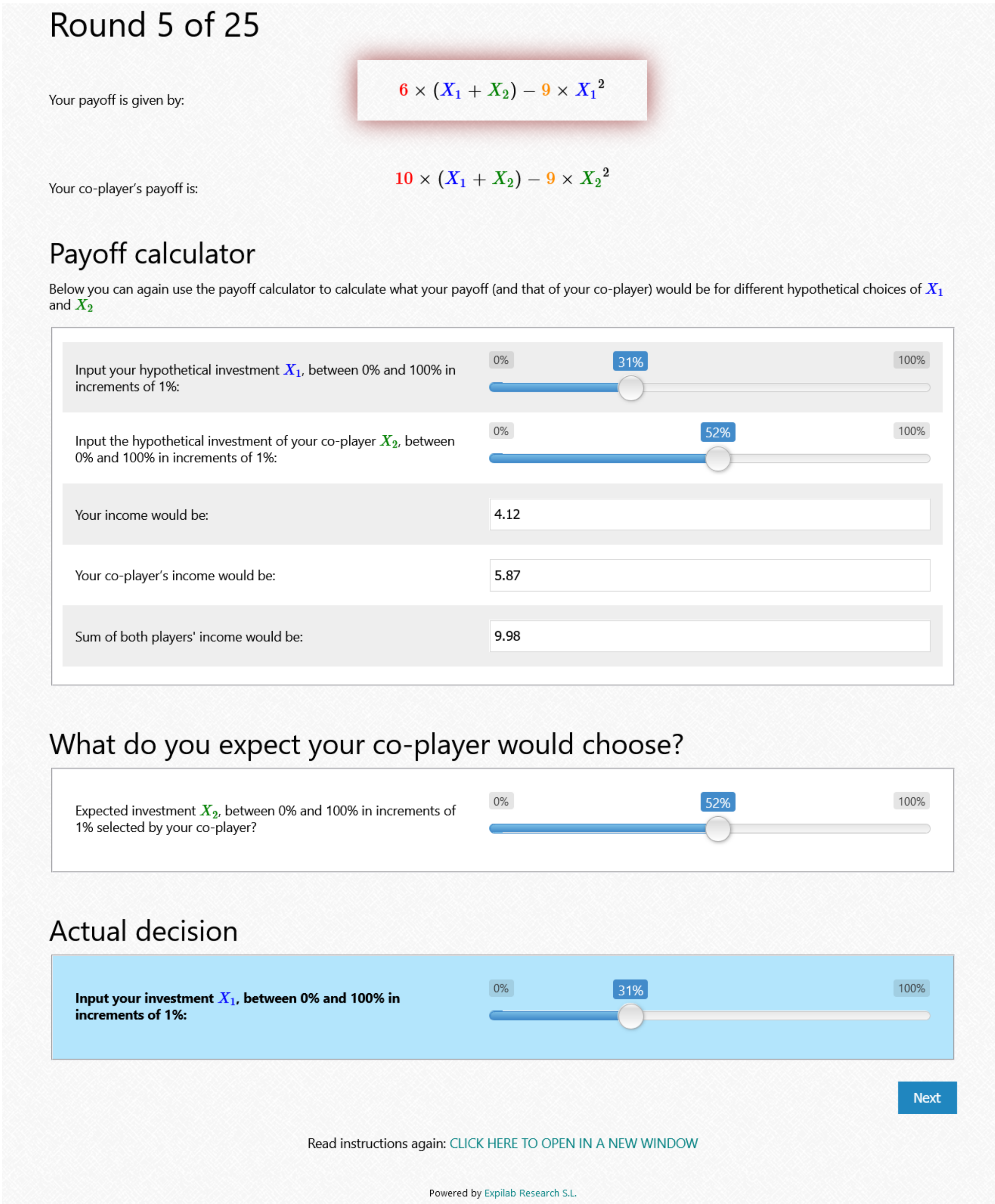
To calculate payoffs, we match each participant with the most recent participant who finished the game prior to them. Specifically, each of the 25 rounds played by the current player is paired with the respective "mirror" game of the last finishing player. For example, a round where the current payer has a benefit parameter of $b_i = 4$ and the other player has $b_j = 10$ is matched with the round, where the previous player had a benefit parameter of $b_i = 10$ and their other player had $b_j = 4$. The first participant of each experimental session has no previous participant to be matched to. This first participant is paired with a "seed player" randomly chosen from the pilot stage.[36] The payoffs for the current player across all 25 rounds are calculated and displayed, with the average payoff being paid out.

[34] In the initial pilot study, no sequence effects were detected, thereby justifying the application of this methodology in the main experiment. Consistent with the pilot findings, the experimental results also show no evidence of sequence effects. Contributions across all 25 game iterations remain stable (see Figure 48 in the Appendix). The ANOVA results were not statistically significant ($p = 0.475$), indicating that there is no evidence for a significant difference in average contributions across the 25 games.

[35] To avoid priming participants with a reference point, no "default value" was preset in the payoff calculator. Participants were required to actively select input values to initiate the calculator's functionality.

[36] In the pilot stage, the seed player was an artificial player who strictly played the contributions in the Nash equilibrium if players only cared for their own payoffs.

Figure 39: Game Interface – Stage 2



Notes: Screenshot of the game interface in one of the 25 rounds in the second stage of the game (screenshot shows the linear treatment, the game interface is analogous in the quadratic treatment). Via sliders, players can enter hypothetical public good contributions in the payoff calculator to calculate the resulting payoffs and submit their own contribution choice and their expectations about the other agent's contribution.

As previously noted, we calibrated both the linear and quadratic treatments so that the public good provision in the Nash equilibrium, if both agents have a benefit parameter of $b_i = 8$, equals $x_i = 0.44$ in both treatments. However, this calibration results in considerably higher payoffs in the quadratic treatment than in the linear treatment (i.e., $\pi_i = 5.33$ in the linear treatment and $\pi_i = 8.49$ in the quadratic treatment when both agents choose $x_i = 0.44$). To account for this difference, we use an "in-game currency" called "monetary units" (MU), which is converted to EUR or GBP at different rates: 2:1 in the linear and 3:1 in the quadratic treatment (e.g., an in-game payoff of $\pi = 12$ would be converted into an actual payoff of 6 EUR in the linear and 4 EUR in the quadratic treatment).

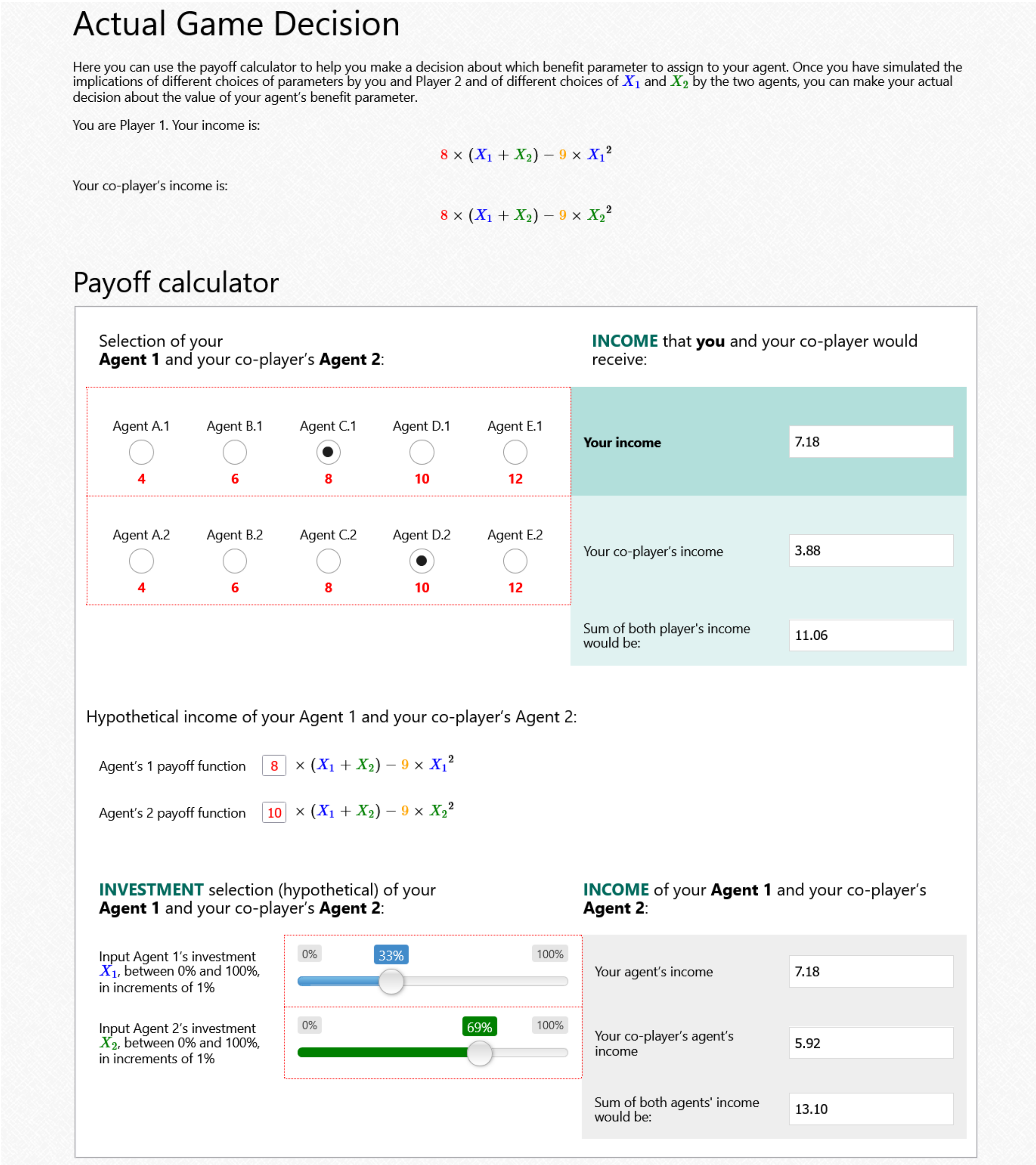
First Stage

In the first stage, participants take on the role of the principal, i.e., they select an agent who decides on the public good contribution on their behalf. They can choose from five different agents who differ only in the benefit parameter that determines their payoffs from the total public good provision. As before, we conduct two treatments, where the benefits from the sum of public good contributions are either linear or quadratic. First-stage experiments follow a similar structure as second-stage experiments. First, participants receive detailed instructions on the game. Next, they complete a tutorial that introduces them to the game interface. The tutorial is particularly designed such that participants can learn that agents' incentives for public good provision increase (decrease) with increasing (decrease) benefit parameters specifying their payoff from public good provision without directly telling them. After successfully completing the tutorial, players are forwarded to the actual game page. They have access to a payoff calculator, that shows the resulting payoffs for all principals and agents for hypothetical choices of agents and their contribution decisions (see Figure 40).[37] Finally, participants are required to select an agent and state their expectations about the other principal's choice of agent and the agents' public good provisions (see Figure 41).

After the game, players complete a questionnaire that gathers demographic information – including age, gender, education level, and degree of mathematical literacy – as well as their attitudes toward trust, risk, and donations. Additionally, we ask them about their hypothetical decisions in a dictator game with the other principal and an ultimatum game with their chosen agent. To calculate payoffs, each participant is first matched with the most recent player who completed the game before them (analogous to the second stage). Then, each of the two first-stage players is paired with a randomly chosen player from the second stage. Based on the principals' chosen agent, we identify the corresponding second-stage game and determine the agents' contributions in that specific game. For example, suppose the current player (referred to as "Principal 1") delegates to an agent with benefit parameter $b_1 = 4$, while the previously completed player they are matched with (called "Principal 2") delegated to an agent with benefit parameter $b_2 = 10$. We then randomly pair both principals with agents from the second-stage treatment. We call the second stage player matched to Principal 1 (2) "Agent 1 (2)". We then retrieve the contribution that Agent 1 made in the second stage of the game, where their own benefit parameter was $b_i = 4$, and the other agent's benefit parameter was $b_j = 10$. Similarly, we identify Agent 2's contribution in the "mirror" game, i.e., the game in which her benefit parameter was $b_i = 10$, and the other player's benefit parameter was $b_j = 4$. On the final page of the session, we inform players of the choices made by the other principal and both agents, displaying the respective payoffs for all four players. The in-game currency is measured in MU and converted to EUR or GBP at a rate of 2:1 in the linear and 3:1 in the quadratic treatment.

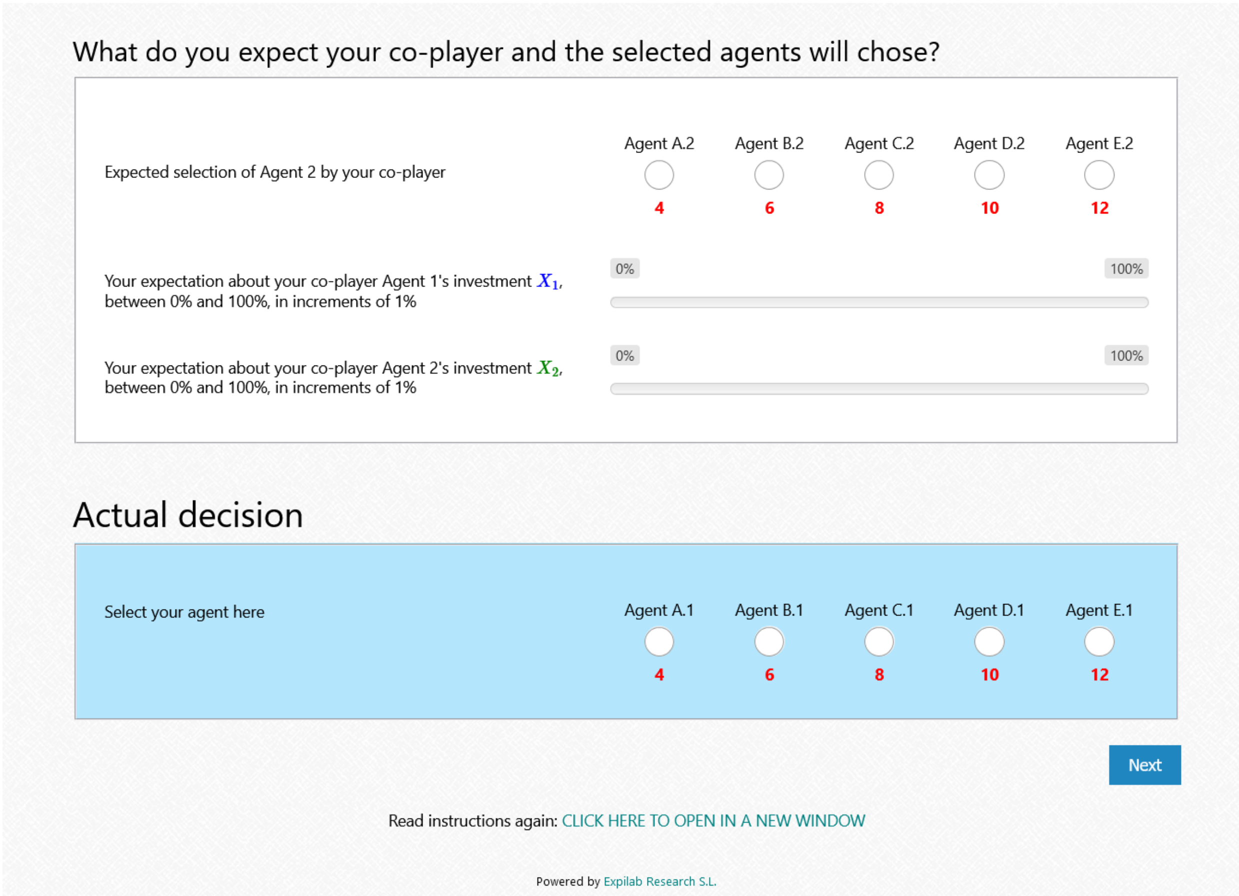
[37] Analogous to Stage 2, we did not provide "default parameters" (see Footnote 35).

Figure 40: Game Interface – Stage 1 (a)



Notes: Screenshot of the upper half of the game interface in the first stage of the game (screenshot shows the linear treatment, the game interface is analogous in the quadratic treatment). Via buttons and sliders, players can enter hypothetical agents, to which they and the other principal delegate, and hypothetical agents' public good contributions in the payoff calculator to calculate the resulting payoffs and submit their own contribution choice and their expectations about the other agent's contribution.

Figure 41: Game Interface – Stage 1 (b)



Notes: Screenshot of the lower half of the game interface in the first stage of the game (screenshot shows the linear treatment, the game interface is analogous in the quadratic treatment). Via buttons and sliders players can submit their own choice of agent and their expectations about other principal's delegation choice and the agents' contribution.

Execution

The experiment was programmed as a browser-based application by Expilab Research and hosted on their servers. Both second-stage treatments were conducted online through Prolific's UK participant pool screening for fluent English proficiency on May 30, 2023 (linear treatment) and June 29, 2023 (quadratic treatment). Participants received a flat participation fee of 4 GBP, in addition to their payoffs from the experiment. For the linear treatment, 145 subjects started the second stage, 38 participants returned the assignment, and two were rejected for not completing the experiment, resulting in 105 completed observations. The median completion time was 26:04 minutes, and the average payoff was 2.79 GBP, implying a total payoff of 6.79 GBP. For the quadratic treatment, 160 subjects began the experiment, 52 returned the assignment, two participants timed out, and one was excluded for incomplete participation, summing up to 105 completed observations. The median time for completion was 27:29 minutes, and the average payoff amounted to 4.09 GBP, implying a total average payoff of 8.09 GBP.

For the second stage, we first conducted an extensive online pilot via Prolific on February 12, 2024, (linear treatment) and February 13, 2024 (quadratic treatment). As before, participants were restricted to Prolific's UK subject pool. Participants received a flat participation fee of 4 GBP in addition to their payoffs from the experiment. Out of 457 subjects starting the linear second-stage treatment, 202 returned the assignment, and two timed out, resulting in 253 completed observations. The median time for completion was 16:17 minutes, and the average payoff amounted to 2.66 GBP, leading to a total payoff of 4.66 GBP. The quadratic second-stage treatment was started by 550 subjects; 291 returned the assignment, six were timed out, and four were rejected because they did not complete the experiment. This resulted in 249 completed observations. The median time for completion was 14:55 minutes, and the average payoff amounted to 2.72 GBP, implying a total average payoff of 4.72 GBP.

Scrutinizing the log data revealed that the large drop-out numbers were mainly due to participants failing the tutorial, as they were kicked out after five mistakes. Since passing the tutorial simply requires careful reading and following instructions, this suggests that the complexity of our first-stage treatment may be ill-suited for online platforms like Prolific. On such platforms, a notable portion of participants may be less engaged with the task compared to those in lab-based experiments.

As a consequence, we ran the first stage treatments as lab experiments from May 22, 2024, to May 24, 2024, in the Bologna Laboratory for Experiments in Social Sciences (BLESS) at the University of Bologna.

3.5 Results

While our primary focus is on the first-stage results, where strategic delegation may occur, we briefly report the results of the second-stage games, which are essentially standard one-shot public goods games.

3.5.1 Second Stage Results

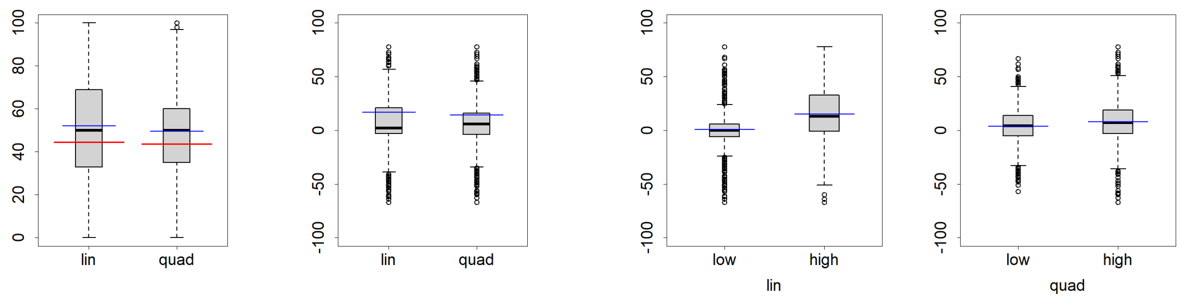
The average contribution across all 25 games in the linear treatment was 0.522 compared to the Nash equilibrium average of 0.444 if agents only care about their own payoffs. In the quadratic treatment, we observe an average contribution of 0.496 compared to a Nash equilibrium contribution of 0.437 (see Panel (a) in Figure 42).[38] The statistically significant deviation from the Nash equilibrium contributions (one-sided Mann-Whitney test, $p = 4.84e^{-16}$ in linear treatment and $p = 7.12e^{-19}$ in quadratic treatment) aligns with expectations if at least some participants are conditional cooperators.

As conditional cooperation is based on a notion of reciprocity, we expect agents to contribute more if they expect higher contributions from the other player. To test this, we divide the sample for each treatment into two subsamples: one where agents have below or equal to the median expectation of the other player's contributions, and one in which agents have above the median expectations (see Panel (b) in Figure 42). In the linear treatment, we find an average deviation of 0.7 percentage points for the low and 14.94 percentage points for the high-expectation group. For the quadratic treatment, the deviations are 3.68 and 8.17 percentage points, respectively. According to one-sided Mann-Whitney tests the mean deviation is in both treatments significantly lower in the low expectation than in the high expectation subsample ($p = 2.18e^{-62}$ for the linear treatment and $p = 1.73e^{-09}$ for the quadratic treatment). Notably, the difference between

[38] For detailed boxplots of contributions and deviations of contributions from the Nash equilibrium of all 25 games in both treatments see Figures 49 and 50 in Appendix A.0.3.

Figure 42: Contributions and Deviations from NE

(a) Contributions and Deviations from NE **(b) Deviations from NE in Subsamples**



Notes: Boxplots of (a) contributions and deviations from the Nash equilibrium pooled over all 25 games in the linear (lin), and quadratic (quad) treatment and (b) deviations from the Nash equilibrium pooled over all 25 games for the two subsamples of below (low) and above (high) median expectation in the linear (lin) and quadratic (quad) treatment. In addition to the median, we indicate means using wider blue lines. In (a) on the left, the red line represents the Nash equilibrium average.

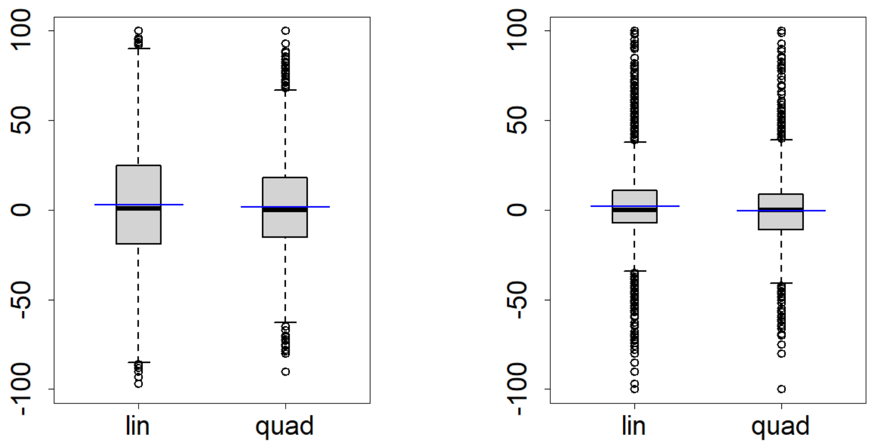
the two subsamples is much larger in the linear compared to the quadratic treatment.[39] This difference arises because, in the quadratic treatment, best responses are strategic substitutes, while they are dominant strategies in the linear treatment. This implies that agents who primarily consider their own payoffs have an incentive to lower their contributions if they anticipate the other agent's contribution to increase. In contrast, in the linear treatment, the best response is independent of the other player's contribution. Consequently, in the high-expectation group, conditional cooperators contribute more than those in the low-expectation subsample, while self-interested players choose lower contributions in the high-expectation subsample than their counterparts in the low-expectation group. This second effect, induced by strategic substitutability in the quadratic treatment, is absent in the linear treatment. When pooled across all 25 games, the impact of conditional cooperation outweighs the effect of strategic substitutability. Our results support previous findings that a significant fraction of players can be classified as conditional cooperators. If this were not the case, we would expect no statistically significant difference in contributions between expectation groups in the linear treatment and a significantly lower level of contributions in the high expectation group in the quadratic treatment.

Additionally, we elicit the accuracy of players' expectations about other players' contributions.[40] To do this, we calculate the absolute differences between each player's expectations and the actual contributions of the other players (left panel in Figure 43). While individual expectation errors can be large (standard deviation $sd = 33.62$ percentage points in the linear and $sd = 27.83$ percentage points in the quadratic treatment) the mean expectation error is significantly positive (two-sided Mann-Whitney test, $p = 1.40e^{-05}$ for the linear and $p = 0.0266$ for the quadratic treatment) but small: 2.75 percentage points in the linear and 1.61 percentage points in the quadratic treatment. This implies that players are, on average, slightly

[39] This can also be seen in the individual games. Detailed boxplots for all 25 games in both treatments are shown in Figure 51 in Appendix A.0.3 We find significantly higher deviations from the NE in the higher expectation subsample in 17 out of the total 25 games in the linear and 8 out of 25 games in the quadratic treatment.

[40] We deliberately did not provide monetary incentives for the elicitation of expectations, based on findings of Gächter and Renner (2010), who show in a repeated public goods game that non-incentivized beliefs were only mildly (but significantly) less accurate than incentivized beliefs, yet incentivized beliefs significantly changed the own contribution choice, while non-incentivized belief elicitation did not.

Figure 43: Contribution Expectation Errors – Stage 2



Notes: Boxplots of the absolute difference between expectations and (i) the other players' actual contributions (left) and (ii) the own contribution choice in the mirror game (right) pooled over all 25 games in the linear (lin) and quadratic (quad) treatment.

too optimistic about other players' contributions.[41]

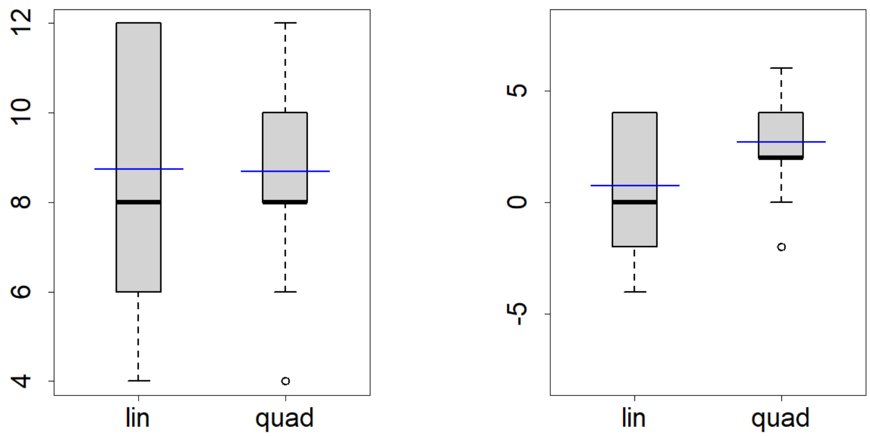
As all participants of the second stage experiments play all 25 games, we can compare their expectations of the other player's contribution to the contribution they make in the "mirror" game, where they play from the other player's perspective (right panel in Figure 43). Although individual differences between expectations and actual contributions in the mirror game can be large (standard deviation $sd = 26.15$ in the linear and $sd = 21.33$ in the quadratic treatment, the average difference is close to zero with 2.21 percentage points in the linear and -0.31 percentage points in the quadratic treatment. However, these differences are statistically significant according to a two-sided Mann-Whitney test: $p = 4.29e^{-05}$ for the linear and $p = 0.0113$ for the quadratic treatment.[42]

3.5.2 *First Stage Results*

In the first stage of the game, players decide on the benefit parameter of the agent to whom they delegate the provision of the public good. In the linear treatment, the average benefit parameter chosen was 8.742 compared to the Nash equilibrium choice of 8 for players focused solely on their own payoffs. In the quadratic treatment, the average benefit parameter was 8.687 compared to the Nash equilibrium choice of a selfish player (see Figure 44). In both treatments the deviation from the predicted Nash equilibrium is statistically significant (one-sided Mann-Whitney test for actual choices being greater than predicted Nash equilibrium choice, $p = 0.00124$ in the linear and $p = 2.35e^{-27}$ in the quadratic treatment). However, the difference in benefit parameter choices across treatments is not significant (one-sided Mann-Whitney test for choice in linear treatment to be greater than in quadratic treatment, $p = 0.474$). Additionally, when conditioning the choice of the benefit parameter on the expected benefit parameter choice of the other

[41] Detailed boxplots for all 25 games and both treatments are given in Figure 52 in Appendix A.0.3.
[42] Detailed boxplots for all 25 games and both treatments are given in Figure 53 in Appendix A.0.3.

Figure 44: Choice of Benefit Parameter



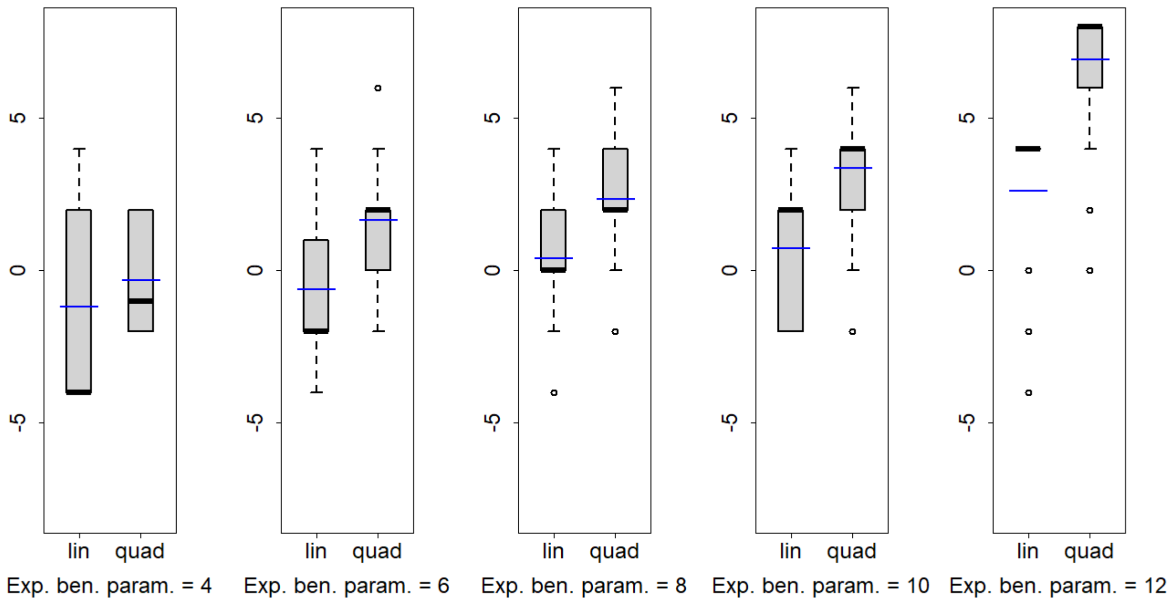
Notes: Boxplots of the benefit parameter choice (left) and its deviation from the predicted Nash equilibrium (right) in the linear (lin) and quadratic (quad) treatment.

player, we do not find significant differences between the benefit parameter choices across both treatments (see Figure 54 and Table 22 in the Appendix). In summary, we have to reject Hypothesis 1, as there is no evidence that players in the quadratic treatment delegate to agents with lower benefit parameters than in the linear treatment. However, we do observe evidence for strategic delegation in both treatments: players choose benefit parameters significantly higher than their own benefit parameters.

To assess whether the evidence for strategic delegation we observe in both treatments is consistent with conditional cooperation, we examine the extent to which players deviate from the best responses of purely self-interested players, given their expectations about the other player's choice of benefit parameter (see Figure 45). Table 17 presents the mean and median deviation for the linear and quadratic treatment. A two-sided Mann-Whitney test indicates that the deviation is significant only for an expected benefit of the other player of 10 and 12 in the linear and for 6–12 in the quadratic treatment. These findings largely support Hypotheses 2 and 3. If players are conditional cooperators, they should deviate from the best response only when they expect the other player to choose a benefit parameter that is above the best response of a selfish player. Accordingly, we would expect the chosen benefit parameter to show a positive deviation from the best response in case of an expected benefit parameter of 10 and 12 in the linear and from 8–12 in the quadratic treatment. Additionally, we expect the deviation to increase with higher expected benefit parameters. Apart from a significant positive deviation for an expected benefit parameter of 6 in the quadratic treatment, our observations exactly align with our expectations regarding conditional cooperation.[43] Thus, our Hypotheses 2 and 3 are confirmed. Our findings clearly indicate that players act as conditional cooperators even in their delegation choices, opting to delegate to agents with higher benefit parameters than they have themselves if they expect the other payer to do the same.

[43]The deviation for an expected benefit parameter of 10 in the linear treatment is significant only at the 10%-significance level.

Figure 45: Deviations Conditioned on Expectation About Other Player



Notes: Boxplot of deviations from best responses conditional on expectations of other player's choice of benefit parameter in linear (left) and quadratic (right) treatment.

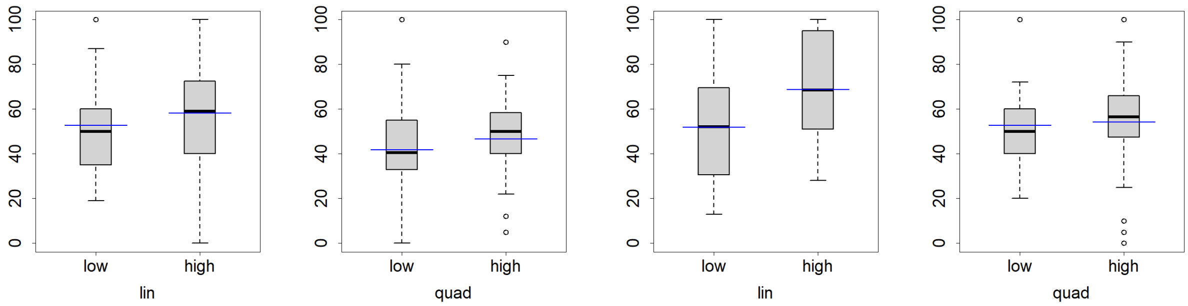
Table 17: Deviation of Benefit Parameters

Exp. ben.	Mean (l)	Median (l)	P-val (l)	Mean (q)	Median (q)	P-val (q)
4	-1.20	-4	0.396	-0.33	-1	0.527
6	-0.63	-2	0.227	1.65	-2	0.005
8	0.39	0	0.108	2.35	2	$1.21e^{-08}$
10	0.71	2	0.074	3.36	4	$6.55e^{-05}$
12	2.62	4	$3.76e^{-05}$	6.92	8	$3.87e^{-06}$

Notes: Mean and median deviation of benefit parameters from best responses of selfish players conditional on the expected benefit parameter of the other player for the linear (l) and quadratic (q) treatment. Two-sided Mann-Whitney tests are performed to test whether the deviation is significantly different from zero (p-val).

Hypothesis 4 states that we expect a rise in the expectation of one's own agent's contribution as the chosen benefit parameter increases (H4a) and that the expectation of the other player's agent's contribution increases with a higher expected benefit parameter chosen by the other principal (H4b). Given the relatively few observations of players choosing or expecting benefit parameters below 8, we pool the data into two groups – benefit parameters below 8 and above 8 – to investigate the expectations about their own agents' contributions. Similarly, for expected contributions by the other player's agent, we pool data by the expected benefit parameters of the other player below and above 8. Figure 46 shows the corresponding boxplots.

Figure 46: Expectation of Agents' Contributions



Notes: Boxplots of the expected contributions in the linear (lin) and quadratic (quad) treatment of the own agent (left) conditioned on whether the choice of the benefit parameter is below (low) or above (high) the own benefit parameter of 8 and the expected contributions of the other agent (right) conditioned on whether the expected choice of the other player's benefit parameter is below (low) or above (high) 8.

We find that the mean and median of expected contributions are consistently higher for benefit parameters or expected benefit parameters above 8 compared to those below 8 (see Table 18). Differences between groups across mean and median in the linear treatments are more pronounced than in the quadratic treatments. This is to be expected, as contributions in the Nash equilibrium for selfish players also increase more steeply with rising benefit parameters in the linear compared to the quadratic treatment. A one-sided Mann-Whitney test on whether the mean of the low benefit parameter subset is lower than the mean of the high subset reveals that only two of the four differences are statistically significant (see column 'p-value' in Table 18). Thus, we find some, though not overwhelming, evidence for Hypothesis 4.

Table 18: Contribution Expectations

	Mean (l)	**Median (l)**	**Mean (h)**	**Median (h)**	**P-value**
Cont. own agent (lin)	52.78	50	58.21	59	0.157
Cont. own agent (quad)	41.85	40.5	46.58	50	0.0836
Cont. other agent (lin)	51.88	52	68.68	68.5	0.00455
Cont. other agent (quad)	52.66	50	54.25	56.5	0.188

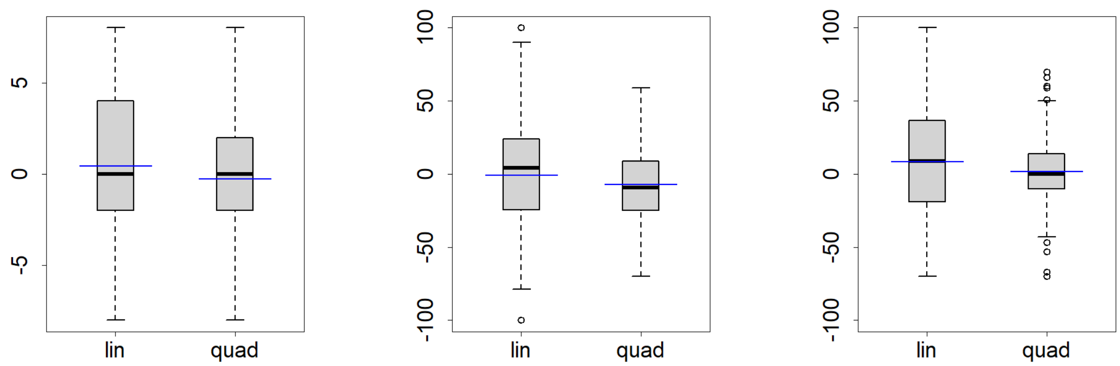
Notes: Mean and median expectations of the contributions of own and the other players' agents in the linear (lin) and the quadratic (quad) treatment for the subsets where (expected) benefit parameters were below 8 (l) or above 8 (h). One-sided Mann-Whitney tests are performed to test whether the high subset mean is significantly higher than the low subset mean (p-value).

We also examine the accuracy of players' expectations regarding the choice of other players' benefit parameters and the contributions of their own and the other players' agents. Figure 47 displays the absolute expectation errors (i.e., the difference between the expected and actual values) for each of the three expectations players were asked to report.[44] We observe that expectation errors are small on average across all three variables and statistically insignificantly different from zero in four out of the six cases, according to a two-sided Mann-Whitney test (see Table 19).

In particular, with respect to the expectation of the other player's choice of benefit parameter, we observe unbiased expectations. Thus, players generally form correct expectations about the benefit parameters

[44]We did not provide monetary incentives for the elicitation of expectations for the same reasons as in Stage 2. See Footnote 40.

Figure 47: Expectation Errors – Stage 1



Notes: Boxplots of the absolute expectation errors in the linear (lin) and quadratic (quad) treatment with respect to other players' choice of benefit parameter (left), own agents' contributions (middle), and contributions of other players' agents (right).

Table 19: Expectation Errors

	Mean (l)	Median (l)	P-val (l)	Mean (q)	Median (q)	P-val (q)
Ben. param.	0.437	0	0.236	−0.269	0	0.337
Cont. own agent	−0.960	4	0.984	−7.16	−9.5	0.00099
Cont. other agent	8.38	9	0.00784	1.81	0	0.409

Notes: Mean and median expectation errors with respect to other players' choice of benefit parameter, own agents' contributions, and contributions of other players' agents in the linear (l) and quadratic (q) treatment. Two-sided Mann-Whitney tests are performed to test whether expectation errors are significantly different from zero (p-val).

chosen by the other players. However, evidence is less definitive for expectations about the public good contributions from their own and the other players' agents. While we observe a slight underestimation of their own agents' contributions (significant only in the quadratic treatment), players slightly overestimate the contributions of the other players' agents (significant only in the linear treatment). In particular, the low average expectation error with respect to the contributions of the other players' agents is somewhat surprising, as it relies on "second-order beliefs". Players have to form expectations about the other players' choice of benefit parameters, which in turn strongly influence the incentives for the other players' agents to contribute to the public good. In summary, the observed expectation errors provide no indication that players misunderstood or failed to anticipate the motivations guiding other players' actions in the first and second stages.

In addition, we run several linear regression models to explore the correlations between dependent variables: the own chosen benefit parameter, the expected benefit parameter of the other agent, the expected contribution of the own agent, and the expected contribution of the other agent alongside other observed data from the experiment, in particular data from our post-experiment questionnaire.[45] The results are shown in Table 20 for the linear and Table 21 for the quadratic treatment.

[45]Screenshots of the post-experiment questionnaire are shown in Figures 55–57 in the Appendix.

In the post-game questionnaire, we specifically asked people about their contribution in a hypothetical (i.e., unincentivized) dictator game and the minimum offer they would accept in a hypothetical ultimatum game.[46] The intention behind these questions was to explore behavioral tendencies related to conditional cooperation and fairness preferences. The level of contribution in the hypothetical dictator game could be an indication of conditional cooperation, i.e., the higher the contribution, the more likely the participant would choose – ceteris paribus – a higher benefit parameter. Similarly, a higher minimum acceptable offer in the hypothetical ultimatum game is an indicator of a participant's aversion to unequal payoffs and the extent to which the participant is willing to forego their own payoff in order to "punish" the other player (as both players receive a payoff of zero in the ultimatum game if the offer is rejected). We hypothesize a negative correlation between the ultimatum game's minimum acceptable offer and the chosen benefit parameter.

Our findings show that that in the linear treatment the correlation between the chosen benefit parameter and the dictator game contribution is positive, while it is negative for the minimum offer in the ultimatum game. In the quadratic treatment, however, both correlations are negative, though none of these effects are statistically significant. Additionally, we find that neither the dictator game contribution nor the minimum acceptable ultimatum game offer significantly explains the expectation about the other players' benefit parameters and the expectations about their own and other agents' contributions in both treatments. Regarding other variables from the questionnaire, we rescale ordinal variables in average, below-average, and above-average values and report the effects of deviations from the average. We excluded age and education, as we did not see sufficient variation in these variables among our lab participants. We observe minimal effects from other demographics. Neither gender nor mathematical literacy are significant in any of the regressions over both treatments. For the other variables, we find occasional effects, which are neither consistent across treatments nor dependent variables. Specifically, we find that in the linear treatment, participants who found the experiment easy to understand chose significantly lower benefit parameters and expected significantly higher benefit parameters from the other player, while in the quadratic treatment participants who found the experiment difficult to understand significantly expected lower benefit parameters from the other player. Further, in the quadratic treatment, participants who reported donating more than the average selected significantly higher benefit parameters, while risk-prone participants expected significantly lower benefit parameters from the other player, and participants with above-average trust expected significantly lower contributions from the other player's agent.[47] However, donation frequency, risk preferences, and trust did not exert a significant influence on the dependent variables in the linear treatment.

We also asked participants about their ideal contribution to the public good if they could directly determine this amount (referred to as ideal own cont.). This ideal own contribution exhibits a significant positive effect on the chosen benefit parameter in the linear treatment and a significant positive effect on the expected contributions of both their own and the other player's agent in both treatments. Moreover, we observe a strong and highly significant effect between the expected benefit parameter and the chosen benefit parameter and vice versa, aligning with the behavior of conditional cooperators (see Hypothesis H3). Additionally, the expected benefit parameter of the other player has a significantly positive effect on the expected contribution of the other player's agent in both treatments, which is in line with Hypothesis (H4b). However, we do not

[46] Screenshots of the questions related to the ultimatum and dictator games are provided in the Appendix, Figure 58.

[47] The results remained robust concerning donation frequency, however, the effects were no longer significant for different categorizations of trust or whether participants are risk-averse.

find a significant positive effect of the participant's chosen benefit parameter on the expected contribution of the own agent in both treatments, which is unexpected. Notably, only the ideal own contribution shows a highly significant effect on the expected contribution of the participant's own agent in both treatments.

Table 20: Regression Analysis - Linear Treatment

Dependent Variable:	Own ben. param.	Other ben. par.	Cont. own agent	Cont. other agent
Model:	(1)	(2)	(3)	(4)
Own ben. param.		0.301***	−0.292	−1.147
		(0.071)	(0.859)	(0.823)
Other ben. param.	0.423***		1.196	2.728***
	(0.099)		(1.013)	(0.951)
Cont. own agent	−0.003	0.009		0.033
	(0.009)	(0.008)		(0.087)
Cont. other agent	−0.013	0.023***	0.035	
	(0.010)	(0.008)	(0.093)	
Ideal own cont.	0.048***	−0.0002	0.302***	0.371***
	(0.010)	(0.009)	(0.104)	(0.098)
Dictator game	0.093	0.036	0.288	−0.724
	(0.200)	(0.169)	(1.920)	(1.851)
Ultimatum game	−0.134	0.106	0.617	−0.553
	(0.236)	(0.199)	(2.264)	(2.184)
Female	0.276	0.096	−0.871	3.102
	(0.401)	(0.339)	(3.845)	(3.700)
Trust – high	0.275	−0.206	−1.125	3.898
	(0.542)	(0.457)	(5.190)	(4.995)
Trust – low	−0.384	0.328	4.096	−1.888
	(0.572)	(0.483)	(5.473)	(5.289)
Math. lit. – high	0.382	0.016	−0.103	5.781
	(0.445)	(0.376)	(4.269)	(4.085)
Math. lit. – low	−0.302	−0.166	−4.783	3.338
	(0.522)	(0.441)	(4.983)	(4.816)
Risk – prone	−0.152	0.503	0.524	−0.669
	(0.557)	(0.468)	(5.328)	(5.140)
Risk – averse	−0.384	0.242	0.436	−2.821
	(0.744)	(0.628)	(7.131)	(6.875)
Donations – high	0.508	−0.018	7.226	3.767
	(0.554)	(0.469)	(5.282)	(5.123)
Donations – low	0.112	0.377	−8.865	−1.116
	(0.703)	(0.593)	(6.687)	(6.496)
Difficulty – high	0.221	−0.224	−1.838	−7.606
	(0.554)	(0.468)	(5.306)	(5.076)
Difficulty – low	−1.283***	0.694*	3.924	−7.289*
	(0.449)	(0.387)	(4.426)	(4.233)
Constant	3.435***	3.506***	23.050**	23.334**
	(1.094)	(0.906)	(10.679)	(10.282)
Observations	142	142	142	142
R^2	0.340	0.293	0.212	0.245
Adjusted R^2	0.250	0.196	0.103	0.142
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: Regression Analysis - Quadratic Treatment

Dependent Variable:	Own ben. param.	Other ben. par.	Cont. own agent	Cont. other agent
Model:	(1)	(2)	(3)	(4)
Own ben. param.		0.532^{***}	-0.282	-1.139
		(0.071)	(0.663)	(0.762)
Other ben. param.	0.670^{***}		0.772	1.514^{*}
	(0.089)		(0.741)	(0.851)
Cont. own agent	-0.006	0.014		0.017
	(0.015)	(0.013)		(0.115)
Cont. other agent	-0.019	0.020^{*}	0.013	
	(0.013)	(0.011)	(0.085)	
Ideal own cont.	0.013	-0.015	0.399^{***}	0.159^{*}
	(0.012)	(0.011)	(0.072)	(0.094)
Dictator game	-0.022	-0.043	-0.467	-0.901
	(0.194)	(0.173)	(1.300)	(1.506)
Ultimatum game	-0.044	-0.003	-1.468	0.749
	(0.218)	(0.194)	(1.453)	(1.693)
Female	0.111	0.416	-1.049	2.368
	(0.424)	(0.376)	(2.844)	(3.293)
Trust – high	-0.604	0.618	-1.417	-9.539^{**}
	(0.536)	(0.476)	(3.612)	(4.086)
Trust – low	-0.075	0.388	-2.068	-1.294
	(0.501)	(0.445)	(3.354)	(3.897)
Math. lit. – high	0.456	-0.403	0.420	3.209
	(0.501)	(0.447)	(3.374)	(3.901)
Math. lit. – low	0.426	-0.110	-1.603	6.114
	(0.505)	(0.451)	(3.391)	(3.892)
Risk – prone	0.548	-0.976^{*}	-2.275	0.440
	(0.560)	(0.492)	(3.767)	(4.378)
Risk – averse	-0.092	-0.747	4.461	7.232
	(0.663)	(0.586)	(4.422)	(5.106)
Donations – high	0.991^{*}	-0.610	-1.769	0.629
	(0.530)	(0.476)	(3.610)	(4.193)
Donations – low	-0.519	-0.305	-0.956	1.135
	(0.837)	(0.746)	(5.619)	(6.520)
Difficulty – high	0.806	-0.925^{*}	-3.546	7.740
	(0.612)	(0.542)	(4.122)	(4.738)
Difficulty – low	0.237	-0.366	4.270	-0.191
	(0.442)	(0.393)	(2.940)	(3.446)
Constant	2.842^{**}	3.726^{***}	25.164^{***}	36.010^{***}
	(1.358)	(1.179)	(8.959)	(10.182)
Observations	120	120	120	120
R^2	0.409	0.444	0.333	0.154
Adjusted R^2	0.311	0.351	0.222	0.013

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.6 Discussion and Conclusions

We presented – to the best of our knowledge – the first experimental evidence of whether and to what extent principals strategically delegate the provision of a public good to agents who hold a different valuation of the public good than they do. In our experimental setting, characterized by complete information, delegating the decision on public good provision to an appropriate agent enables principals to credibly commit to either a higher or a lower level of public good provision than they would select themselves. When benefits from public good provision are strictly concave, public good provision choices are strategic substitutes. In this case, principals who solely care about their own payoff have an incentive to delegate to agents with a lower valuation of the public good than their own. This incentive, however, is absent when public good provision choices are dominant strategies.

Thus, we conducted two treatments of a delegation-based public good experiment: one where benefits from public good provision were linear (rendering public good contributions dominant strategies), and another where the benefits were strictly concave (rendering public good choices strategic substitutes). Consistent with findings in the experimental literature, we observe that both principals and agents are not only motivated by their own payoffs; rather, their actions align with conditional cooperation. Specifically, they contribute more to the public good if they expect the other agent to do the same, and they delegate to an agent with a higher valuation of the public good if they expect the other principal will do likewise.

We observe significant differences in conditional cooperation behavior across treatments in the public good provision stage (Stage 2), attributable to the strategic substitutability of public good choices in the quadratic treatment. However, we do not observe these differences in the delegation stage (Stage 1). In both treatments, principals choose, on average, agents that have a higher valuation of the public good than they do themselves. Although the difference between the linear and quadratic treatment shows the expected sign (higher in the linear treatment), it remains statistically insignificant. This suggests that conditional cooperation is overriding the incentive to strategically delegate to agents with lower public good evaluation. One hypothesis that may explain the result is based on the following observation. Contrary to Hypothesis H4, we find, at most, weak evidence that principals expect higher public good contributions if they delegate to agents with a higher public good valuation (see Tables 18, 20 and 21). However, the incentive for strategic delegation is inherently linked to the expectation that agents with a higher public good valuation, ceteris paribus, contribute more. If principals do not anticipate a significant change in the agent's contribution with varying valuation of the public good, there is also no incentive to strategically delegate. Additionally, it is noteworthy that principals' expectations regarding agent's public good provisions are – at least on average – mostly accurate (see Figure 47 and Table 19). While our Stage 2 data clearly demonstrates increasing public good provisions with increasing benefit parameters (see Figure 49), it is interesting that the positive deviation from the Nash equilibrium contribution of selfish players is more pronounced for low than for high benefit parameters (see Figure 50).

Non-linear public goods games introduce complexity, as public good contributions are no longer dominant strategies, requiring players to form expectations about the contributions of others. The complexity increases for principals during the delegation stage, as they have to form beliefs not only about the other principal's choice of agent but also about how these choices will influence the agents' public good provision in the second stage. To facilitate comprehension, our experiments began with an extensive tutorial to familiarize players with the game interface. Additionally, the interface included a payoff calculator, allowing players to compute their own payoffs and those of all other players for any hypothetical action profile. Despite these measures, we cannot rule out that principals did not fully comprehend the complete ramifications of their choice of agents, particularly with respect to strategic delegation.

In terms of implementation, we leveraged the game's sequential structure for a novel implementation protocol that allows us to (i) execute the two game stages independently and (ii) collect data within each stage sequentially, eliminating the need for the two agents, respectively two principals, competing against each other to be present simultaneously. Importantly, this implementation design is not limited to our particular delegation public goods game; it is, in principle, adaptable to all multistage games where decisions at each stage are made simultaneously by all players (i.e., without observing the decision of the other players).

While we are cautious about generalizing our findings from the specific set-up of our delegation-based public goods game to delegation in public goods contexts in general, our results suggest that inefficiencies due to strategic delegation may be less problematic, as individuals in real-world settings are less prone to strategic delegation than economic theory predicts. Future research could, therefore, explore to what extent our results hold in other experimental set-ups involving delegation in public good provision contexts, as well as investigate the underlying drivers for the (lack of) incentive to strategically delegate.

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Appendix

A.0.1 Subgame Perfect Equilibrium of Delegation Public Goods Game

The Nash equilibrium of the second stage is given by the simultaneous solution of the first-order conditions (4) for both agents $i = 1, 2$. By assumption, C' is strictly increasing. As a consequence, the inverse function exits and we can re-arrange the first-order condition (4) to yield:

$$x_i = C'^{-1}\big(\theta_i B'(x)\big) \,, \qquad i = 1, 2 \,. \tag{A.1}$$

Summing up equations (A.1) for both agents yields an implicit equation for the amount of total public good provision in the Nash equilibrium:

$$x = C'^{-1}\big(\theta_1 B'(x)\big) + C'^{-1}\big(\theta_2 B'(x)\big) \,. \tag{A.2}$$

Due to the inverse function theorem, we obtain:

$$\frac{d}{dx}\Big(C'^{-1}\big(\theta_i B'(x)\big)\Big) = \frac{\theta_i B''(x)}{C''\Big(C'^{-1}\big(\theta_i B'(x)\big)\Big)} \leq 0 \,. \tag{A.3}$$

Thus, the right-hand side of equation (A.2) is decreasing in x, while the left-hand side is strictly increasing. As a consequence, there exists a unique level of x in the Nash equilibrium of the second stage of the game, which via equations (A.1) translate into unique individual good contributions x_1 and x_2. We denote the total and individual public good contributions of this unique Nash equilibrium of the second stage by $x(\Theta)$ and $x_i(\Theta)$ ($i = 1, 2$).

Public good provision choices are either strategic substitutes ($B'' < 0$) or dominant strategies ($B'' = 0$), as the implicit function theorem yields:

$$\frac{dx_i}{dx_{-i}} = \frac{\theta_i B''(x)}{C''(x_i) - \theta_i B''(x)} \leq 0 \,, \qquad i = 1, 2 \,. \tag{A.4}$$

To derive the comparative statics of second stage NE with respect to θ_i, we re-arrange the first-order conditions (A.1):

$$F_i = x_i - C'^{-1}\big(\theta_i B'(x_i + x_{-i})\big) = 0 \,, \tag{A.5}$$

$$F_{-i} = x_{-i} - C'^{-1}\big(\theta_{-i} B'(x_i + x_{-i})\big) = 0 \,, \tag{A.6}$$

where $i, j = 1, 2$ and $j \neq i$. Total differentiation yields:

$$dF_i = \frac{\partial F_i}{\partial \theta_i} d\theta_i + \frac{\partial F_i}{\partial x_i} dx_i + \frac{\partial F_i}{\partial x_{-i}} dx_{-i} = 0 \,, \tag{A.7}$$

$$dF_{-i} = \frac{\partial F_{-i}}{\partial \theta_i} d\theta_i + \frac{\partial F_{-i}}{\partial x_i} dx_i + \frac{\partial F_{-i}}{\partial x_{-i}} dx_{-i} = 0 \,. \tag{A.8}$$

Thus, we obtain:

$$\frac{dx_i}{d\theta_i} = -\frac{\frac{\partial F_i}{\partial \theta_i}\frac{\partial F_{-i}}{\partial x_{-i}} - \frac{\partial F_{-i}}{\partial \theta_i}\frac{\partial F_i}{\partial x_{-i}}}{\frac{\partial F_i}{\partial x_i}\frac{\partial F_{-i}}{\partial x_{-i}} - \frac{\partial F_i}{\partial x_{-i}}\frac{\partial F_{-i}}{\partial x_i}} = \frac{B'\left(C'' - \theta_{-i}B''\right)}{C''\left(C'' - \theta_{-i}B''\right) - \theta_i B'' C''} > 0 \,, \tag{A.9}$$

$$\frac{dx_{-i}}{d\theta_i} = \frac{\frac{\partial F_i}{\partial \theta_i}\frac{\partial F_{-i}}{\partial x_i} - \frac{\partial F_{-i}}{\partial \theta_i}\frac{\partial F_i}{\partial x_i}}{\frac{\partial F_i}{\partial x_i}\frac{\partial F_{-i}}{\partial x_{-i}} - \frac{\partial F_i}{\partial x_{-i}}\frac{\partial F_{-i}}{\partial x_i}} = \frac{\theta_{-i} B' B''}{C''\left(C'' - \theta_{-i}B''\right) - \theta_i B'' C''} < 0 \,. \tag{A.10}$$

In addition, it holds:

$$\frac{dx}{d\theta_i} = \frac{dx_i}{d\theta_i} + \frac{dx_{-i}}{d\theta_i} = \frac{B'C''}{C''\left(C'' - \theta_{-i}B''\right) - \theta_i B''C''} > 0\,. \tag{A.11}$$

Assuming that the cost and benefit functions are at least "almost quadratic", i.e. $B''' \approx 0$ and $C''' \approx 0$, we obtain:

$$\frac{d^2x}{d\theta_i^2} = \frac{B'B''\left(C''\right)^2}{\left[C''\left(C'' - \theta_{-i}B''\right) - \theta_i B''C''\right]^2} < 0\,, \tag{A.12}$$

$$\frac{d^2x_i}{d\theta_i^2} = \frac{B'B''\left(C'' - \theta_{-i}B''\right)C''}{\left[C''\left(C'' - \theta_{-i}B''\right) - \theta_i B''C''\right]^2} < 0\,, \tag{A.13}$$

$$\frac{d^2x_{-i}}{d\theta_i^2} = \frac{\theta_{-i}B'\left(B''\right)^2 C''}{\left[C''\left(C'' - \theta_{-i}B''\right) - \theta_i B''C''\right]^2} > 0\,. \tag{A.14}$$

In the first stage, the principals' first-order conditions are given by:

$$B'\big(x(\Theta)\big)\frac{dx(\Theta)}{d\theta_i} - C'\big(x_i(\Theta)\big)\frac{dx_i(\Theta)}{d\theta_i} = 0\,, \qquad i = 1, 2\,. \tag{A.15}$$

Taking the first-order condition (4) of the second stage into account, we can simplify equation (A.15) to yield:

$$(1-\theta_i)B'\big(x(\Theta)\big)\frac{dx(\Theta)}{d\theta_i} = -C'\big(x_i(\Theta)\big)\frac{dx_{-i}}{d\theta_i}\,, \qquad i = 1, 2\,. \tag{A.16}$$

Inserting the formulae for $dx_i(\Theta)/d\theta_i$, $dx_i(\Theta)/d\theta_i$ and $dx_{-i}(\Theta)/d\theta_i$ into equation (6), we can explicitly solve for the reaction function of principal i:

$$\theta_i(\theta_{-i}) = \frac{C''\big(x_{-i}(\Theta)\big)}{C''\big(x_{-i}(\Theta)\big) - \theta_{-i}B''\big(x(\Theta)\big)}\,. \tag{A.17}$$

Assuming that the cost and benefit functions are almost quadratic, i.e. $B''' \approx 0$ and $C''' \approx 0$, we obtain:

$$\frac{d\theta_i(\theta_{-i})}{d\theta_{-i}} = \frac{B''\big(x(\Theta)\big)C''\big(x_{-i}(\Theta)\big)}{\big[C''\big(x_{-i}(\Theta)\big) - \theta_{-i}B''\big(x(\Theta)\big)\big]^2} \leq 0\,. \tag{A.18}$$

Thus, also the principals' choices of the payoff parameters θ_i are either strategic substitutes (in case of a strictly concave benefit function) or dominant strategies (if the benefit function is linear).

A.0.2 Particular Functional Forms

In the following, we explore the SPE for the two special cases where benefits are either linear or quadratic in the provision of the public good.

Liner Benefit Function

We assume the following functional forms:

$$B(x) = bx\,, \qquad C(x_i) = \frac{1}{2}cx_i^2\,. \tag{A.19}$$

Defining $a = b/c$, the first-order condition of the second stage implies that public good provision choices are dominant strategies:

$$x_i = \theta_i a \; . \tag{A.20}$$

In addition, we obtain:

$$\frac{dx_i}{d\theta_i} = a \; , \quad \frac{dx_{-i}}{d\theta_i} = 0 \; , \qquad \frac{dx}{d\theta_i} = a \; . \tag{A.21}$$

The first-order condition of the first stage implies that self-representation, i.e. $\theta_i = 1$, is a dominant strategy:

$$(1 - \theta_i)ab = 0 \qquad \Rightarrow \qquad \theta_i = 1 \; . \tag{A.22}$$

As a consequence, the outcome in the unique SPE of the game is given by:

$$\theta_i = 1 \; , \quad x_i = a \; , \qquad i = 1, 2 \; . \tag{A.23}$$

Quadratic Benefit Function

We assume the following functional forms:

$$B(x) = bx \left(\bar{x} - \frac{1}{2}x \right) \; , \qquad C(x_i) = \frac{1}{2}cx_i^2 \; , \tag{A.24}$$

where $\bar{x}$ denotes the bliss point of public good provision. Employing, again, the definition $a = b/c$, the first-order condition of the second stage yields:

$$x_i = a\theta_i(\bar{x} - x) \; , \tag{A.25}$$

which implies the following best response of agent i

$$x_i(x_{-i}) = \frac{a\theta_i(\bar{x} - x_{-i})}{1 + a\theta_i} \; , \tag{A.26}$$

given the public good provision of the other agent, x_{-i}. Obviously, public good provision choices are strategic substitutes:

$$\frac{x_i(x_{-i})}{dx_{-i}} = -\frac{a\theta_i}{1 + a\theta_i} \; . \tag{A.27}$$

Summing up the first-order conditions (A.25) of both agents $i = 1, 2$, yields the total public good provision in the second stage of the game:

$$x = \bar{x}\frac{a(\theta_1 + \theta_2)}{1 + a(\theta_1 + \theta_2)} \; . \tag{A.28}$$

Inserting back into the first-order condition yields the public good provision of agent i:

$$x_i = \bar{x}\frac{a\theta_i}{1 + a(\theta_1 + \theta_2)} \; . \tag{A.29}$$

In addition, we obtain the comparative statics with respect to θ_i:

$$\frac{dx_i}{d\theta_i} = \bar{x}\frac{a\left(1+a(\theta_1+\theta_2)\right)}{\left[1+a(\theta_1+\theta_2)\right]^2} > 0\,, \tag{A.30a}$$

$$\frac{dx_{-i}}{d\theta_i} = -\bar{x}\frac{a^2(\theta_1+\theta_2)}{\left[1+a(\theta_1+\theta_2)\right]^2} < 0\,, \tag{A.30b}$$

$$\frac{dx}{d\theta_i} = \bar{x}\frac{a}{\left[1+a(\theta_1+\theta_2)\right]^2} > 0\,. \tag{A.30c}$$

The first-order condition of the first stage yields:

$$(1-\theta_i)a(\bar{x}-x)\frac{dx}{d\theta_i} = -x_i\frac{dx_{-i}}{d\theta_i}\,, \tag{A.31}$$

which implies the following best response function of principal i

$$\theta_i(\theta_{-i}) = \frac{1}{1+a\theta_{-i}}\,, \tag{A.32}$$

for a given θ_{-i} of the other principal. Also, the preference choice parameters in the first stage are strategic substitutes:

$$\frac{d\theta_i}{d\theta_{-i}} = -\frac{a}{(1+a\theta_{-i})^2} \tag{A.33}$$

Solving, for the subgame perfect θ_i yields:

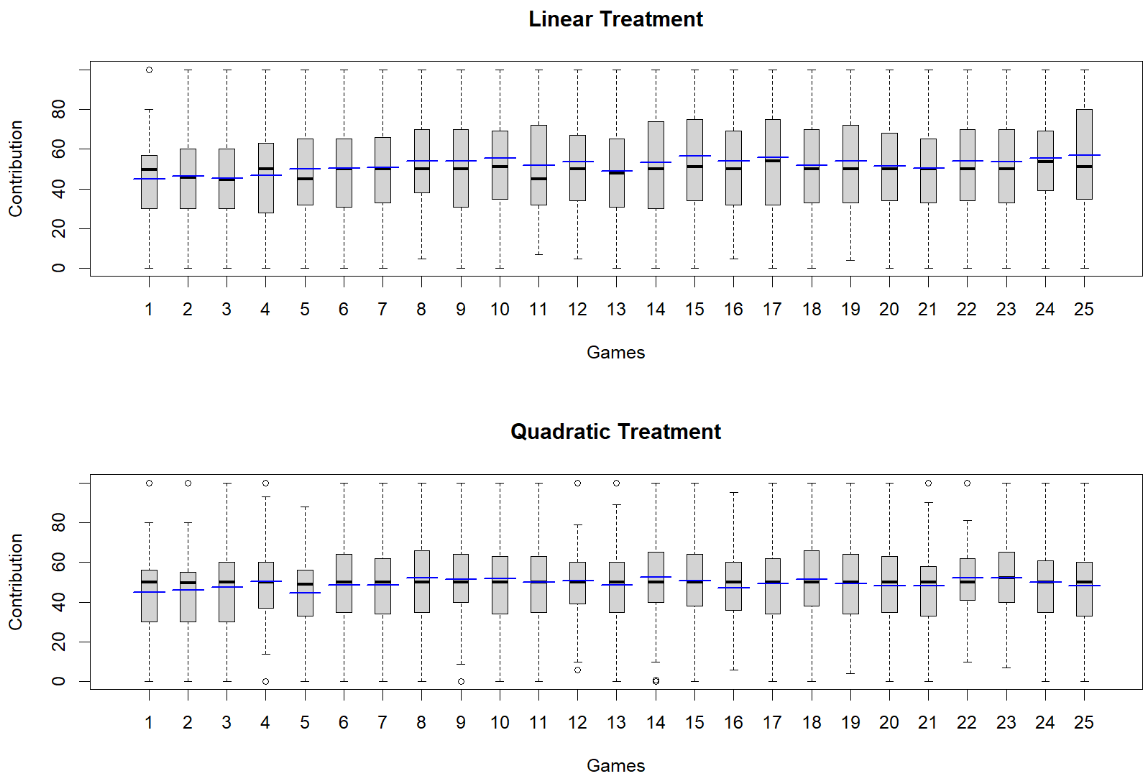
$$\theta_i = \frac{\sqrt{1+4a}-1}{2a}\,, \qquad i = 1,2\,. \tag{A.34}$$

Thus, we obtain for the outcome in the subgame perfect equilibrium:

$$\theta_i^\star = \frac{\sqrt{1+4a}-1}{2a}\,, \qquad x_i^\star = \bar{x}\frac{a\theta_i^\star}{1+2a\theta_i^\star}\,, \qquad i = 1,2\,. \tag{A.35}$$

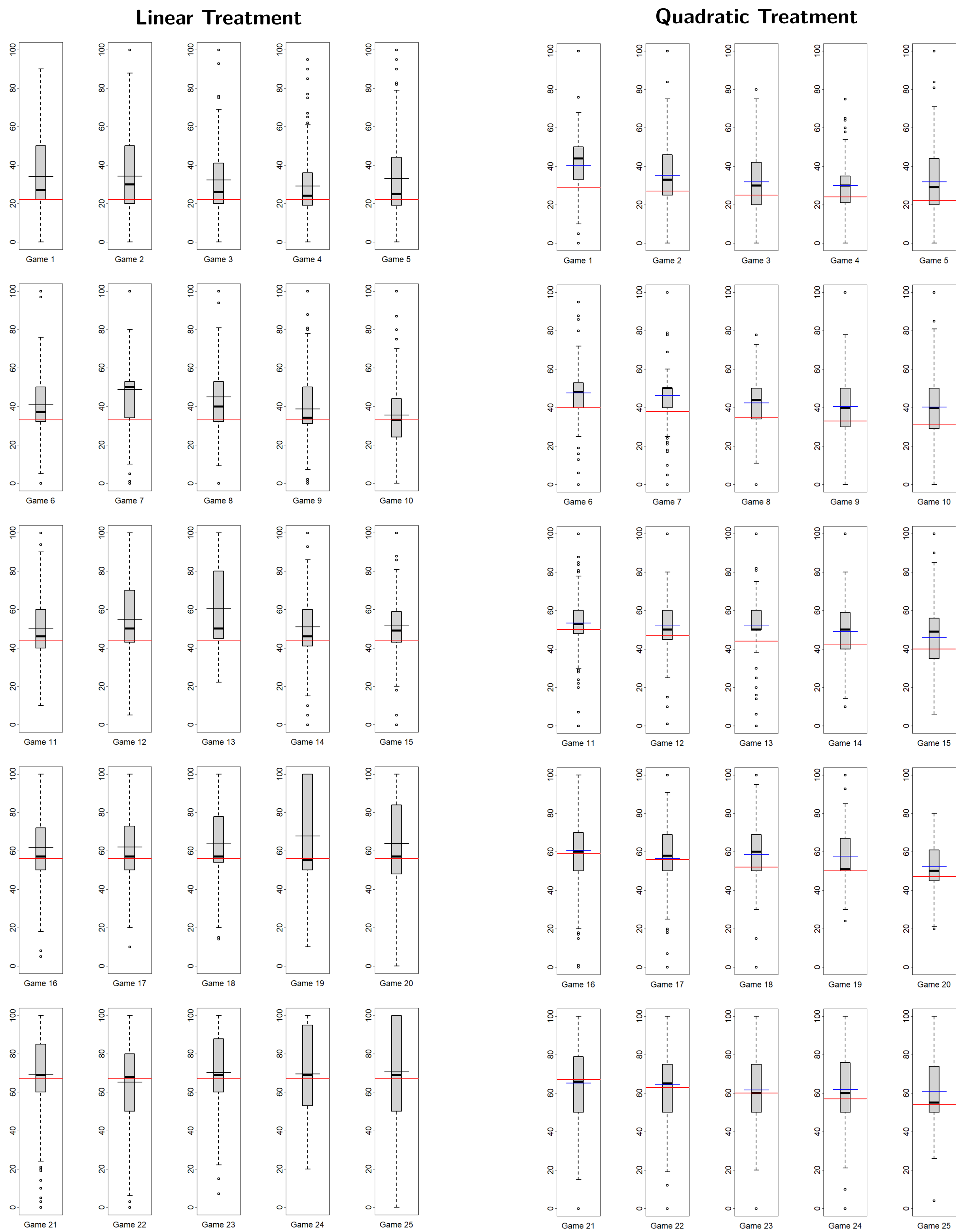
A.0.3 Additional Results for Stage 2

Figure 48: Contribution Sequence



Notes: Boxplots illustrating contributions across the 25 one-shot games for both the linear treatment (upper panel) and quadratic treatment (lower panel). In each plot, the mean contribution is indicated by a blue line for comparative reference.

Figure 49: Players' Contributions

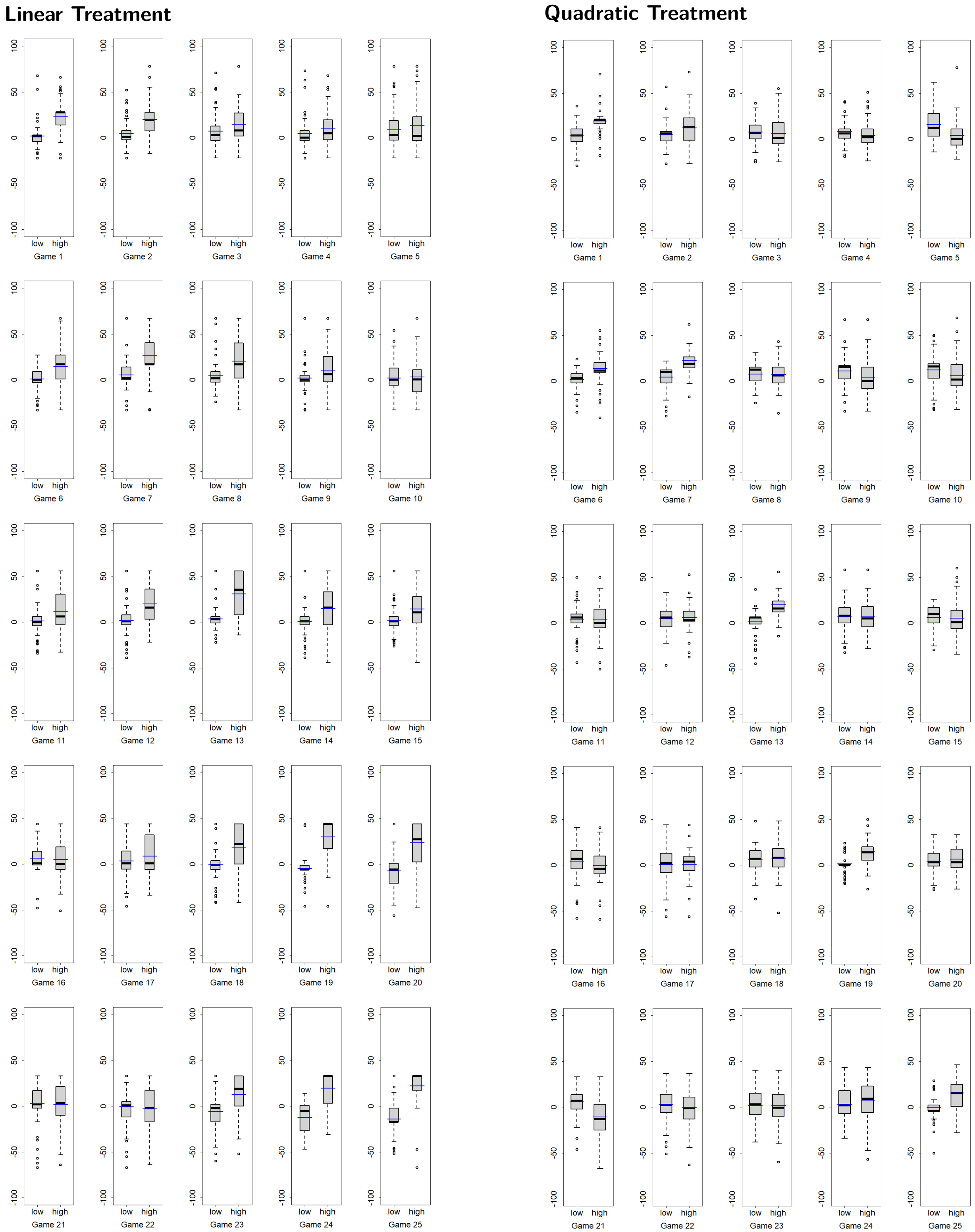


Notes: Boxplots of players' contributions in the 25 second stage games in the linear (left) and quadratic (right) treatment. Red lines indicate contributions in the Nash equilibrium if agents only care about their own monetary payoffs.

Figure 50: Players' Contributions (Difference to NE)

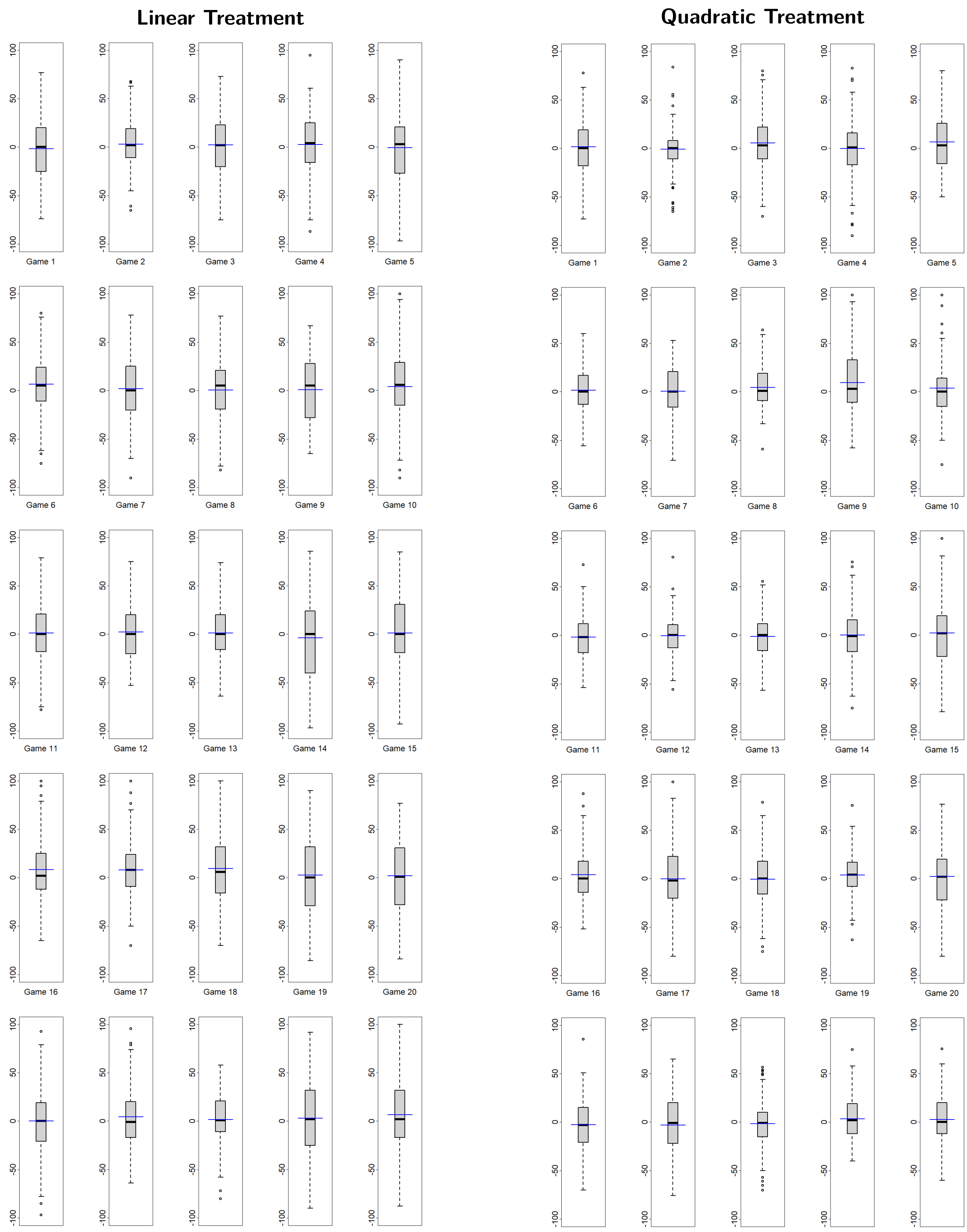
Notes: Boxplots of the difference between players' contributions and the contributions in the Nash equilibrium if agents only care about own monetary payoffs in the 25 second stage games in the linear (left) and quadratic (right) treatment.

Figure 51: Players' Contributions (Expectation Subsamples)



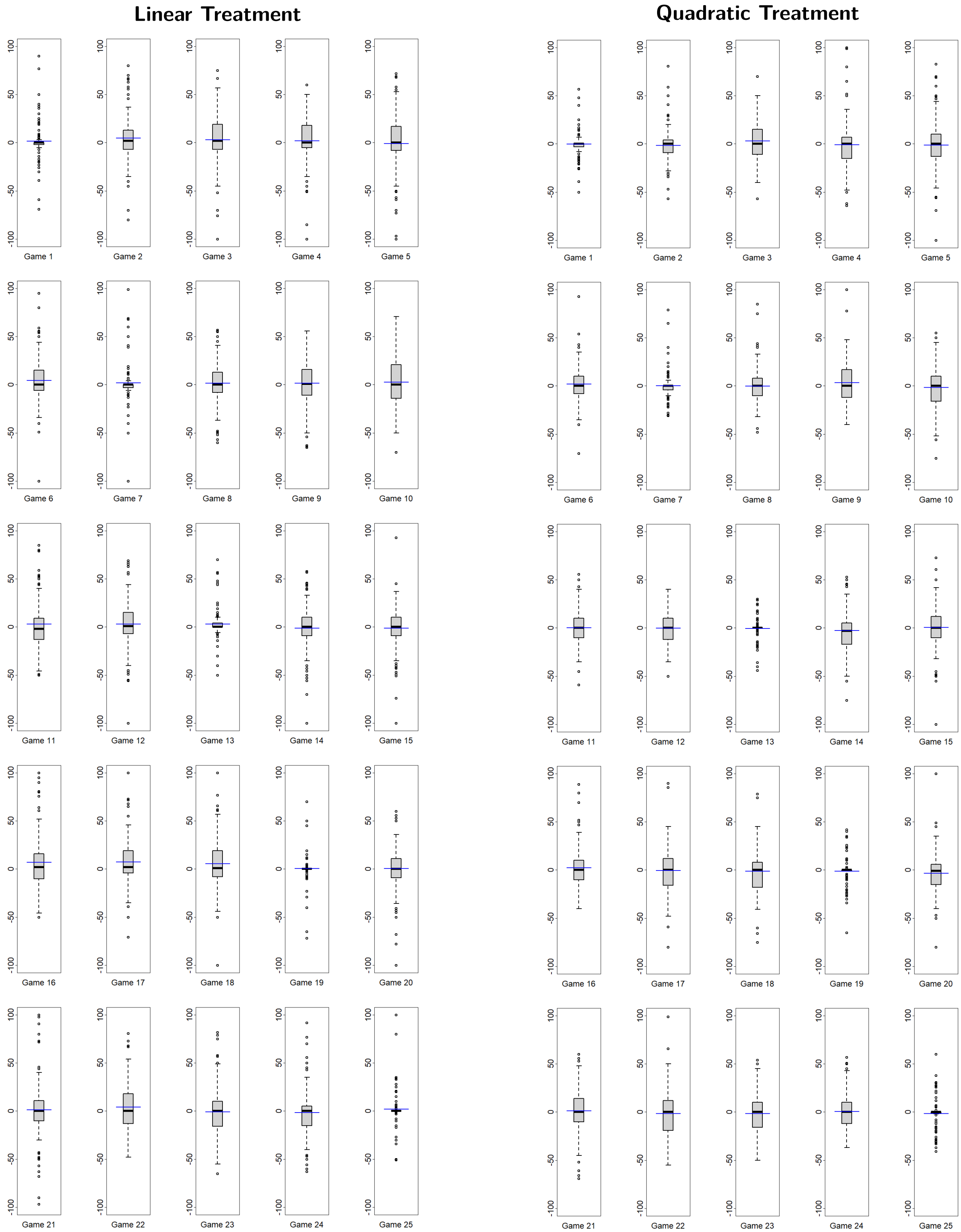
Notes: Boxplots of the difference between players' contributions and the contributions in the Nash equilibrium if agents only care about their own monetary payoffs for the two subsamples of below (low) and above (high) median expectation in the 25 second stage games in the linear (left) and quadratic (right) treatment.

Figure 52: Players' Expectations and Contributions (Actual Games)



Notes: Boxplots of difference between players' expectations and other player's actual contributions in the 25 second stage games in the linear (left) and quadratic (right) treatment.

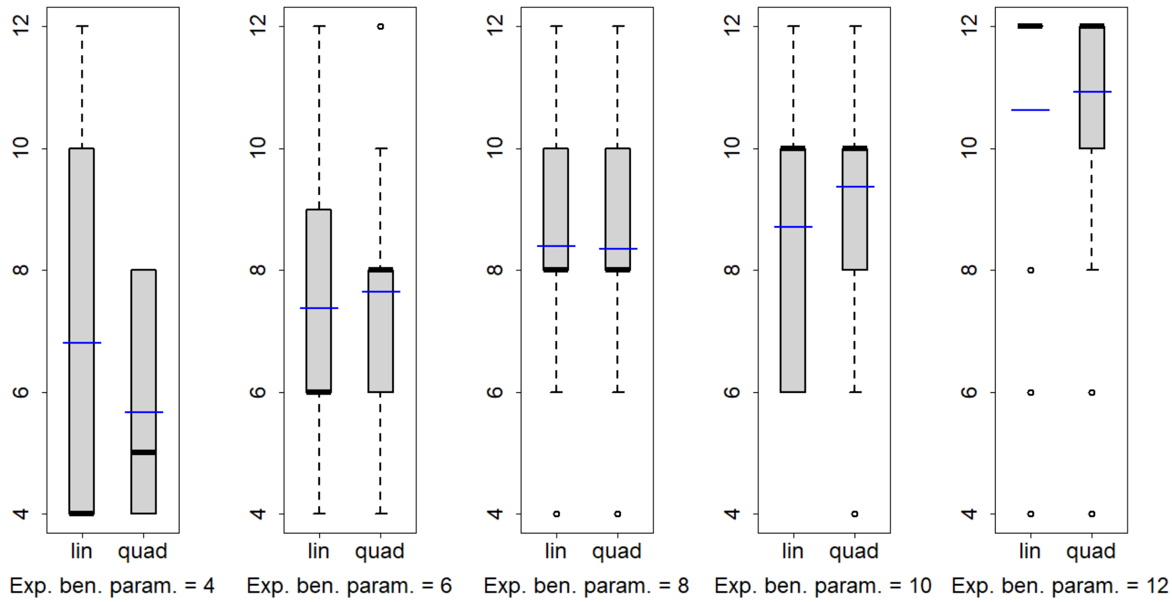
Figure 53: Players' Expectations and Contributions (Mirror Games)



Notes: Boxplots of difference between players' expectations and their own contribution in the corresponding "mirror game" in the 25 second stage games in the linear (left) and quadratic (right) treatment.

A.0.4 Additional Results for Stage 1

Figure 54: Benefit Parameter Conditioned on Expectation About Other Player



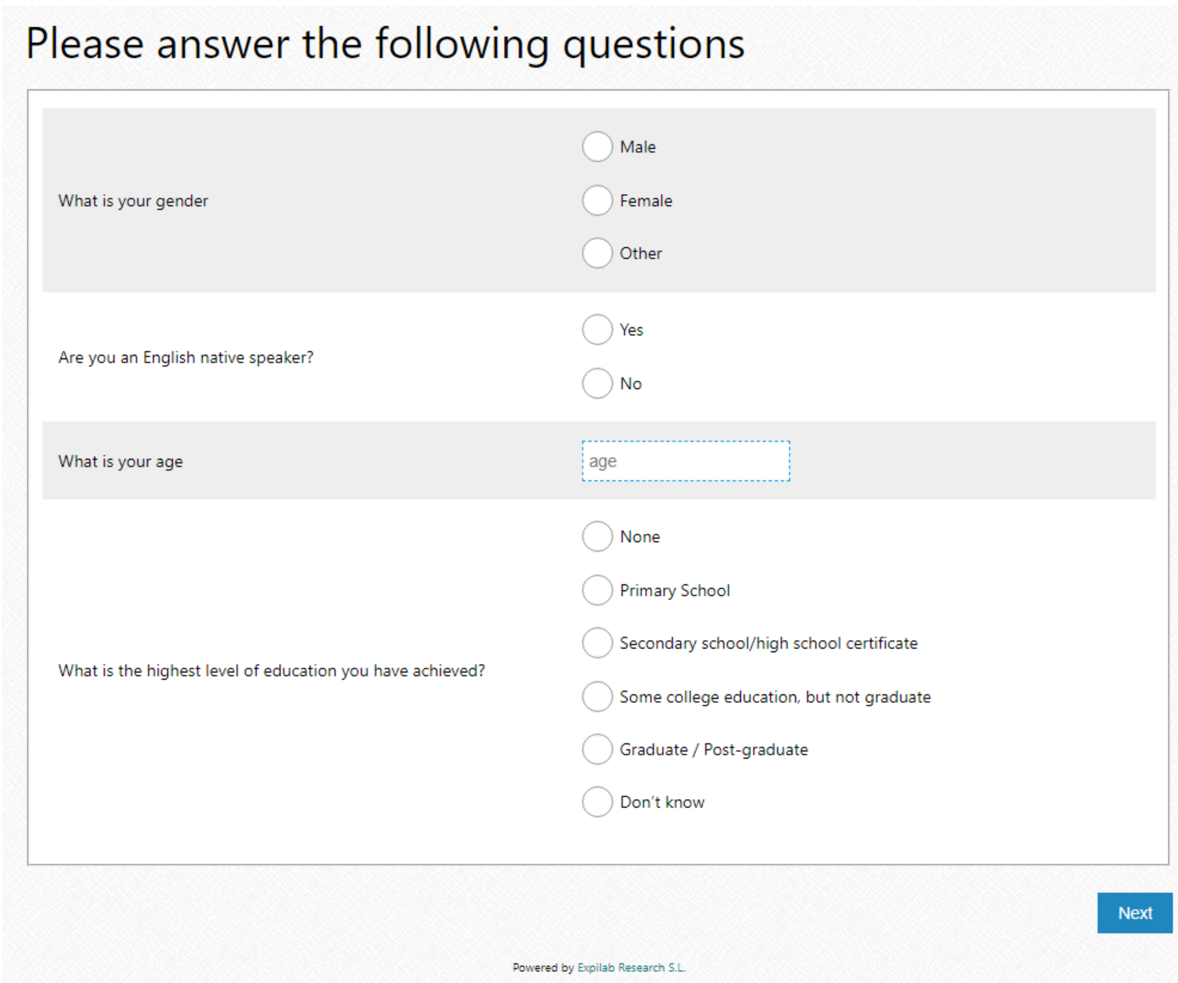
Notes: Boxplot of benefit parameters conditioned on expectations of other player's benefit parameter in linear (left) and quadratic (right) treatment.

Table 22: Benefit Parameter Conditioned on Expectation About Other Player

Exp. ben.	Mean (lin)	Median (lin)	Mean (quad)	Median (quad)	P-value
4	6.80	4	5.67	5	0.7300
6	7.37	6	7.65	8	0.5953
8	8.39	8	8.35	8	0.8676
10	8.71	10	9.36	10	0.2418
12	10.62	12	10.92	12	0.8840

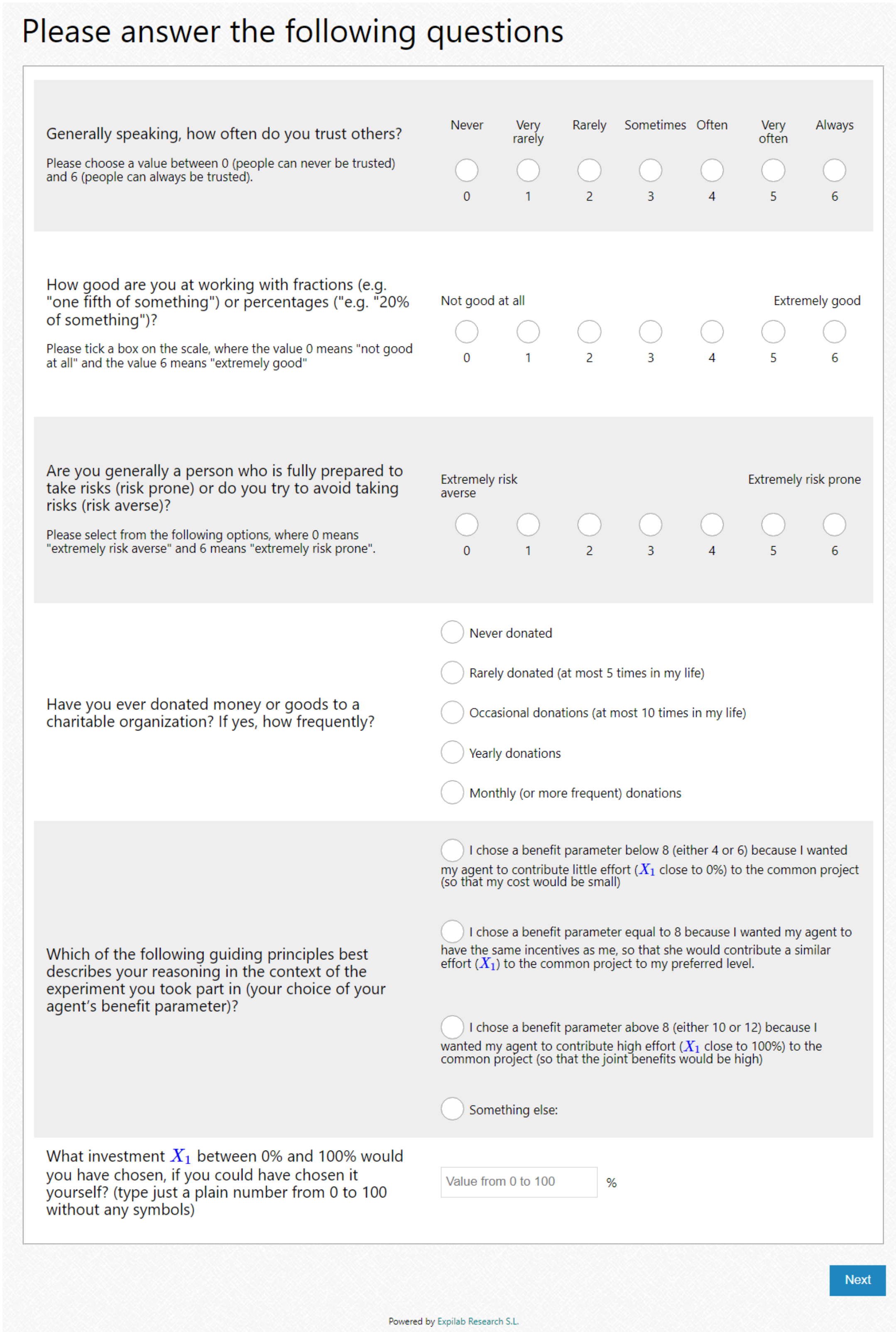
Notes: Mean and median benefit parameters conditional on the expected benefit parameter of the other player for the linear (lin) and quadratic (quad) treatment. The difference between the means in linear and quadratic treatment is not significant according to a two-sided Mann-Whitney test.

Figure 55: Questionnaire [1]



Notes: Screenshot of the first page of the post-experiment questionnaire, which includes questions regarding gender, English proficiency, age, and level of education.

Figure 56: Questionnaire [2]



Please answer the following questions

Generally speaking, how often do you trust others?

Please choose a value between 0 (people can never be trusted) and 6 (people can always be trusted).

Never	Very rarely	Rarely	Sometimes	Often	Very often	Always
0	1	2	3	4	5	6

How good are you at working with fractions (e.g. "one fifth of something") or percentages ("e.g. "20% of something")?

Please tick a box on the scale, where the value 0 means "not good at all" and the value 6 means "extremely good"

Not good at all — Extremely good

0 1 2 3 4 5 6

Are you generally a person who is fully prepared to take risks (risk prone) or do you try to avoid taking risks (risk averse)?

Please select from the following options, where 0 means "extremely risk averse" and 6 means "extremely risk prone".

Extremely risk averse — Extremely risk prone

0 1 2 3 4 5 6

Have you ever donated money or goods to a charitable organization? If yes, how frequently?

- Never donated
- Rarely donated (at most 5 times in my life)
- Occasional donations (at most 10 times in my life)
- Yearly donations
- Monthly (or more frequent) donations

Which of the following guiding principles best describes your reasoning in the context of the experiment you took part in (your choice of your agent's benefit parameter)?

- I chose a benefit parameter below 8 (either 4 or 6) because I wanted my agent to contribute little effort (X_1 close to 0%) to the common project (so that my cost would be small)
- I chose a benefit parameter equal to 8 because I wanted my agent to have the same incentives as me, so that she would contribute a similar effort (X_1) to the common project to my preferred level.
- I chose a benefit parameter above 8 (either 10 or 12) because I wanted my agent to contribute high effort (X_1 close to 100%) to the common project (so that the joint benefits would be high)
- Something else:

What investment X_1 between 0% and 100% would you have chosen, if you could have chosen it yourself? (type just a plain number from 0 to 100 without any symbols)

Value from 0 to 100 %

Next

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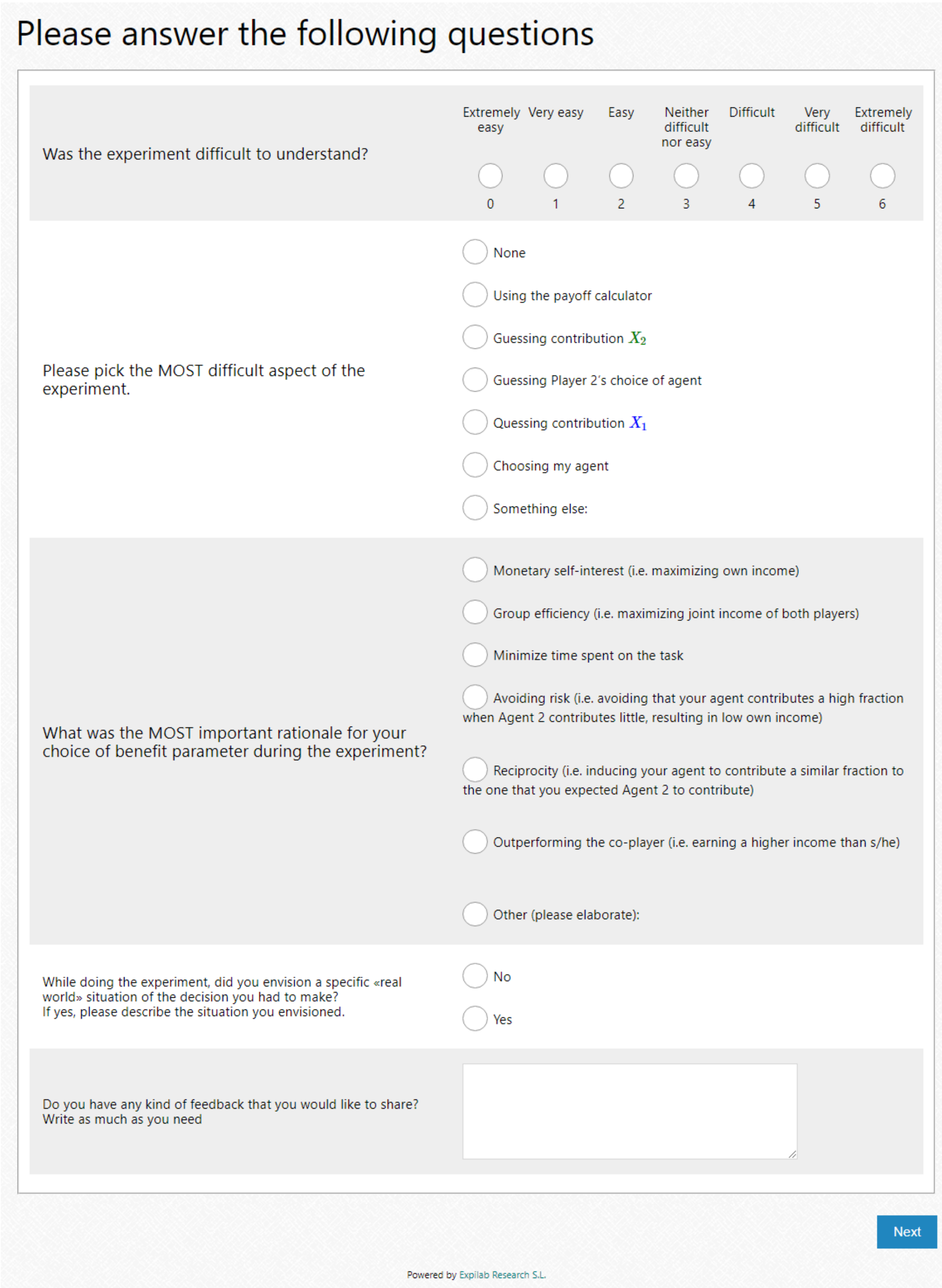
Notes: Screenshot of the second page of the post-experiment questionnaire, containing questions regarding trust, mathematical literacy, risk preferences, donation behavior, guiding principle, and their own ideal contribution.

Figure 57: Questionnaire [3]



Please answer the following questions

Was the experiment difficult to understand?	Extremely easy	Very easy	Easy	Neither difficult nor easy	Difficult	Very difficult	Extremely difficult
	0	1	2	3	4	5	6

Please pick the MOST difficult aspect of the experiment.

- None
- Using the payoff calculator
- Guessing contribution X_2
- Guessing Player 2's choice of agent
- Quessing contribution X_1
- Choosing my agent
- Something else:

What was the MOST important rationale for your choice of benefit parameter during the experiment?

- Monetary self-interest (i.e. maximizing own income)
- Group efficiency (i.e. maximizing joint income of both players)
- Minimize time spent on the task
- Avoiding risk (i.e. avoiding that your agent contributes a high fraction when Agent 2 contributes little, resulting in low own income)
- Reciprocity (i.e. inducing your agent to contribute a similar fraction to the one that you expected Agent 2 to contribute)
- Outperforming the co-player (i.e. earning a higher income than s/he)
- Other (please elaborate):

While doing the experiment, did you envision a specific «real world» situation of the decision you had to make?
If yes, please describe the situation you envisioned.

- No
- Yes

Do you have any kind of feedback that you would like to share?
Write as much as you need

Next

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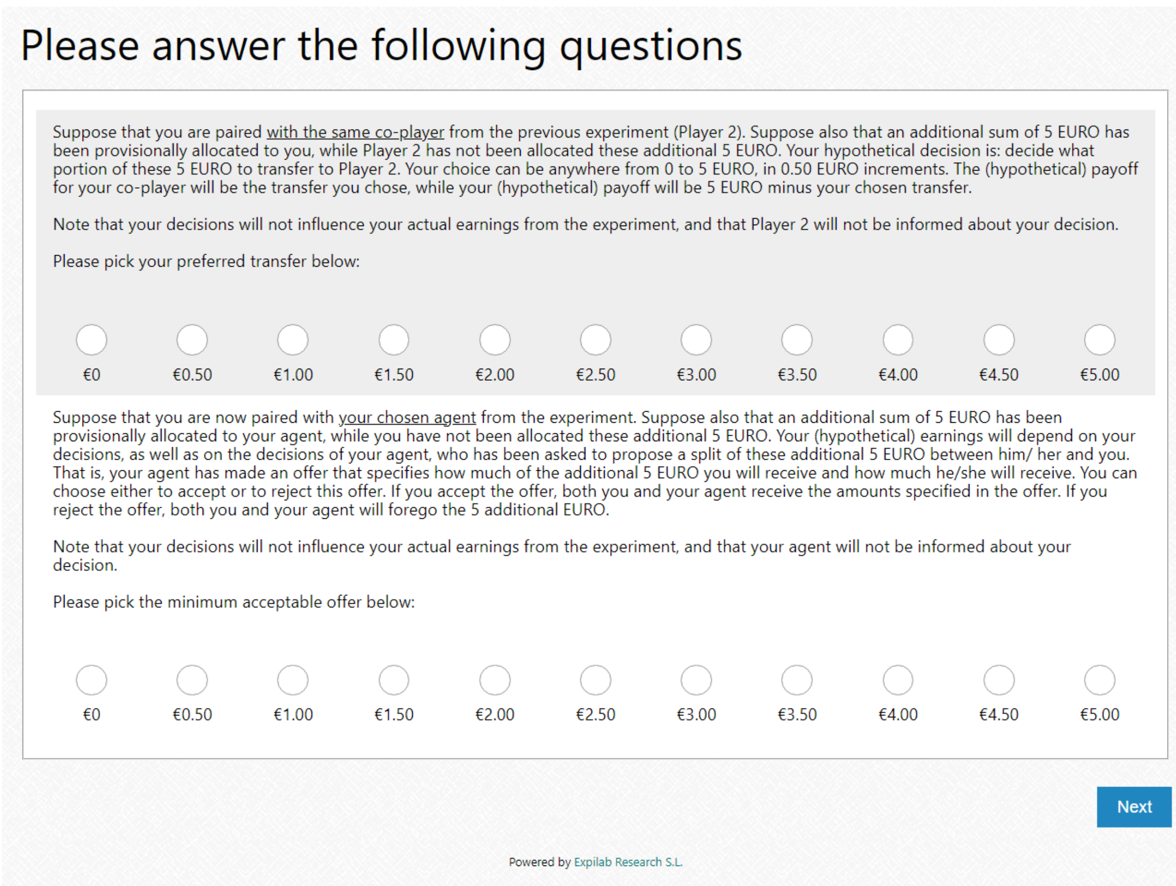
Notes: Screenshot of the third page of the post-experiment questionnaire, featuring questions on the perceived difficulty of understanding the experiment, the rationale behind the participants' choices, scenario envisionment, and an open question for feedback.

Figure 58: Questionnaire [DG, UG]



Please answer the following questions

Suppose that you are paired with the same co-player from the previous experiment (Player 2). Suppose also that an additional sum of 5 EURO has been provisionally allocated to you, while Player 2 has not been allocated these additional 5 EURO. Your hypothetical decision is: decide what portion of these 5 EURO to transfer to Player 2. Your choice can be anywhere from 0 to 5 EURO, in 0.50 EURO increments. The (hypothetical) payoff for your co-player will be the transfer you chose, while your (hypothetical) payoff will be 5 EURO minus your chosen transfer.

Note that your decisions will not influence your actual earnings from the experiment, and that Player 2 will not be informed about your decision.

Please pick your preferred transfer below:

€0 €0.50 €1.00 €1.50 €2.00 €2.50 €3.00 €3.50 €4.00 €4.50 €5.00

Suppose that you are now paired with your chosen agent from the experiment. Suppose also that an additional sum of 5 EURO has been provisionally allocated to your agent, while you have not been allocated these additional 5 EURO. Your (hypothetical) earnings will depend on your decisions, as well as on the decisions of your agent, who has been asked to propose a split of these additional 5 EURO between him/ her and you. That is, your agent has made an offer that specifies how much of the additional 5 EURO you will receive and how much he/she will receive. You can choose either to accept or to reject this offer. If you accept the offer, both you and your agent receive the amounts specified in the offer. If you reject the offer, both you and your agent will forego the 5 additional EURO.

Note that your decisions will not influence your actual earnings from the experiment, and that your agent will not be informed about your decision.

Please pick the minimum acceptable offer below:

€0 €0.50 €1.00 €1.50 €2.00 €2.50 €3.00 €3.50 €4.00 €4.50 €5.00

Next

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Notes: Screenshot of the fourth page of the post-experiment questionnaire, presenting the two questions on the hypothetical ultimatum and dictator games.

Selbstständigkeitserklärung

Ich erkläre hiermit, dass ich diese Arbeit selbstständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche gekennzeichnet. Mir ist bekannt, dass andernfalls der Senat gemäss Artikel 36 Absatz 1 Buchstabe o des Gesetzes vom 5. September 1996 über die Universität zum Entzug des aufgrund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, Friday 8th November, 2024

Anna Schmid