Identifying the Extent of Farm-Level Climate Change Adaptation

by Julian Zeilinger, Andreas Niedermayr, Abdul Quddoos, and Jochen Kantelhardt

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Julian Zeilinger[1], *Andreas Niedermayr*[1], *Abdul Quddoos*[2] *and Jochen Kantelhardt*[1]

[1]*University of Natural Resources and Life Sciences, Vienna, Institute of Agricultural and Forestry Economics, Austria*

[2]*Government College University Faisalabad, Department of Economics, Pakistan*

Corresponding author email: julian.zeilinger@boku.ac.at

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Abstract:

Adaptation to climate change in agriculture is a key goal in order to mitigate its effects. The Ricardian method has been used extensively to account for adaptation within impact assessment. Yet, it follows the relatively strict assumption of farms being perfectly adapted to climate. Building on upcoming evidence of potential limitations of adaptation we relax this assumption and analyse climate change adaptation at the farm-level. Our findings overall depict imperfect adjustment to climate change of Austrian farms and therefore contradict the concept of perfect adaptation. Moreover, our results suggest that potential gains of additional adaptation will become substantively higher with future climate change and thus call for further development and implementation of effective farm-level adaptation measures.

Keywords: climate change, agriculture, econometrics, adaptive capacity, austria

JEL Codes: Q54, Q12, Q15

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1 Introduction

Agriculture is an economic sector which is highly influenced by climate change and thus requires integrated responses in order to mitigate its impacts (IPCC, 2014). Consequently, member states of the European Union explicitly identify agriculture as one of their priority sectors, and many are applying specific measures to improve climate change adaptation (EEA, 2019). Yet, a crucial factor is that various measures of adaptation are only implementable in the medium- or long-term, making unanticipated year-to-year weather fluctuations much more harmful (Moore and Lobell, 2014). When assessing climate change impacts it is thus important to account for the possibility of adaptation, deriving unbiased long-run effects of climate change on agricultural outcome (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007). The transition between those full and mitigated impacts represents adaptation and should be seen as a process (Vanschoenwinkel et al., 2016), as complex adjustments at the farm-level in terms of behaviour and technology (Tol et al., 2004) are required. Hence, there is upcoming evidence that farms are not responding sufficiently to climate change (Burke and Emerick, 2016; Schlenker and Roberts, 2009). Still, contrary to recent findings, challenges and barriers of adaptation are mostly neglected and the underlying assumption of perfectly adjusted farms is predominant within most of the impact analysis studies (Bozzola et al., 2018; Van Passel et al., 2017; Mendelsohn et al., 1994). For a better understanding of future impacts of climate change on agriculture it is therefore crucial to investigate the extent to which climate adaptation at the individual farm-level actually occurs.

Over the last decades, accounting for adaptation has been an important issue within the assessment of climate change impacts on agriculture (Carter et al., 2018). Yet, since it evolves with time, capturing adjustment in a correct way is challenging (Auffhammer, 2018). While farms are expected to be harmed much more by unforeseen weather in the short-run, they adjust practises and use available resources according to the experienced climate change, mitigating impacts over the long-run (Moore and Lobell, 2014). One of the most used methods to identify those mitigated long-run impacts is the Ricardian method, introduced by Mendelsohn et al. (1994). The Ricardian method relies on cross-sectional variation to measure the impact of climate change on farmland productivity. The identification of long-run impacts arises from the assumption that farmers maximise the agricultural outcome given a certain climate they are facing and that each farmer could equally adapt to another farmer's climate. Hence, this method implies that each farm perfectly adapts to changing climatic conditions in the long-run. Although the Ricardian approach is an appealing method to fully incorporate available adaptation of farms, many concerns have been raised due to weak causal inference (Schlenker et al., 2005; Darwin, 1999). A main criticism of using the cross-sectional approach is potential omitted-variable bias, occurring if any variable not considered in the model is correlated with both, climatic measures and outcome (Blanc and Schlenker, 2017). Consequently, resulting estimates will be then confounded.

To overcome this issue, another strand of literature relies on the panel approach (Welch et al., 2010; Deschênes and Greenstone, 2007; Auffhammer et al., 2006). This method uses repeated observations of individuals (e.g. farms) to capture inter-annual variation in agricultural outcomes and meteorological variables to estimate the impact of climate change (Deschênes and Greenstone, 2007). By introducing unit-specific and time-period fixed-effects some of the concerns with omitted-variable bias are addressed, as (un)observed time-invariant and periodic influences are captured in the model (Auffhammer, 2018). However, if weather variables enter the regression linearly, econometric identification within panel data model arises solely from within-unit year-to-year fluctuations in weather and outcome of interest. Therefore, this method is generally acknowledged to capture only impacts based on short-run adjustments to weather fluctuations rather than long-run adaptation (Auffhammer, 2018; Carter et al., 2018). Consequently, an extension of the panel method has been proposed, by employing a second-order polynomial of weather in the regression model (Schlenker et al., 2013). Within this framework, econometric identification is based on both, within-unit variation as well as cross-sectional variation in meteorological variables. Therefore, studies deriving impact estimates from a non-linear panel specification have argued it allows to capture adaptation (Burke et al., 2015; Auffhammer and Schlenker, 2014; Lobell, Schlenker et al., 2011). However, Mérel and Gammans (2018) have recently shown that including non-linearities can reflect long-run values, but only in the case of cross-sectional variation dominating the location-specific weather fluctuations. Therefore, solely relying on non-linearities in a panel data framework may not be sufficient to adequately capture long-run adaptation.

Going one step further, another approach aims to combine the benefits of the Ricardian method and panel data methods (Cui et al., 2019; Mérel and Gammans, 2018; Moore and Lobell, 2014; McIntosh and Schlenker, 2006, Kelly et al., 2005). It utilises the fact that panel data contains both, variation in climate and weather. Therefore, changes in the outcome variable can be split up into differences in climate and random fluctuations around climate (i.e. weather). Quddoos (2020) and Moore and Lobell (2014) use a model of this form to jointly estimate long-run responses based on cross-sectional variation in climate and short-run responses based on inter-annual weather variation. Hence, a major benefit of this method is to identify impacts while considering adaptation and accounting for omitted variable bias. However, this approach still relies on the assumption of perfect adaptation (Moore and Lobell, 2014). By contrast, recent studies suggest that perfect adaptation might not prevail. For example, works by Burke and Emerick (2016) and Schlenker and Roberts (2009) compare short- and long-run responses for corn yields, based on cross-sectional and panel data methods, respectively, and find similar impacts of climate change, indicating little to no adaptation.

In line with these findings, an emerging field of literature attempts to account for the various factors influencing the process of adaptation, and thus acknowledges possible limits (Smit and Wandel, 2006, Brooks et al., 2005; Yohe and Tol, 2002). In particular, determinants of adaptation capability are studied by introducing the concept of adaptive capacity. According to the Intergovernmental Panel on Climate Change (IPCC) 'adaptive capacity is the ability or potential of a system to respond successfully to climate variability and change, and it includes adjustments in both behaviour and in resources and technologies' (IPCC, 2007: 21). At the level of the individual farm, all of these factors are required to adequately respond to climate change. For example, if a farmer is well aware of a changing climate at his site but has not enough resources to employ adequate measures, implementation of adaptation strategies will be lacking. Hence, adaptive capacity of individuals is crucial in order to successfully adapt to climate change (Wamsler and Brink, 2015). Hence, potential limits of adaptation have to be considered, in order to avoid incorrect assumptions about adaptation measures available to farms (Vanschoenwinkel et al., 2020). Studies investigating the long-run effects of climate change on agriculture, simply assuming perfect adaptation thus might derive biased impacts. Therefore, an assessment of adaptation implementation feasibility is critical, to provide a full picture of vulnerability to climate change (Füssel and Klein, 2006).

Consequently, Carter et al. (2018) point out that the extent of climate change adaptation remains an empirical question, and thus requires further methodological developments.

Considering the aforementioned, recent developments the present study contributes to the existing literature in several ways: First, to the best of our knowledge, we are the first to consider potential limitations of climate change adaptation at the farm-level. By introducing a novel panel data framework, different levels of adaptation are simultaneously accounted for. In contrast to the conventional Ricardian method this allows us to relax the assumption of perfect adaptation and further test for its presence. In a second step, this framework determines the extent of adaptation, representing the degree of imperfect adaptation, and its relationship with changing climate.

In what follows, Section 2 introduces the concept of imperfect adaptation at the farm-level and describes how to identify the extent of adaptation. Section 2 further establishes a econometric framework which jointly captures different adjustments and thus the extent of adaptation. Next, Section 3 explains the data used. Section 4 and 5 present and discuss the results, respectively. The final section concludes the paper.

2 Methods

The main objective of this paper is to determine climate change adaptation at the farm-level by accounting for potential limitations of adjustment. Methodologically, we first need to establish an economic model which allows us to identify both states, perfect adaptation, assumed by the Ricardian method, and imperfect adaptation, expected if farms are not able to fully adjust (Section 2.1). Further, we establish an econometric framework which captures different adaptation, using variation in climate and weather jointly. Comparing the adaptation then allows us to assess whether the assumption of perfect adaptation holds. If farms are imperfectly adjusted the resulting difference can be interpreted as the extent of adaptation (Section 2.2).

2.1 Conceptual Framework

A major concern of this paper is to assess climate change adaptation at the farm-level. As set out before, recent studies have shown that perfect, profit maximising adaptation to climate change might not prevail (Burke and Emerick, 2016; Schlenker and Roberts, 2009), as it assumes optimal autonomous adjustment rather than a dynamic process of implementation (Vanschoenwinkel et al., 2016). However, the ability to undertake adaptation can be influenced by a broad set of various factors, including financial and technological resources, as well as information and awareness to manage those resources accordingly (Smit and Wandel, 2006, Brooks et al., 2005; Yohe and Tol, 2002). Yet, the Ricardian method mostly ignores limiting factors of farm-level climate change adaptation (Vanschoenwinkel et al., 2020). The framework employed particularly accounts for common limitations of adaptation. Corresponding to adaptive capacity literature, we assume that the ability of adjusting to climate is determined by various factors, such as information, resources and technology, affecting all farms in certain regions equally. For example, if farms only partially possess information about climate change, or if they lack resources, we expect actual adjustments to be lagging behind and differing from perfect adaptation. We therefore aim to relax the assumption of perfect long-term adaptation to climate underlying the Ricardian method and investigate whether perfect adaptation at the individual farm-level is actually present.

To define the concept of adaptation more formally, assume that farmers choose a production function to maximise the value of agricultural activity (V), while facing specific conditions for climate, weather, soil, and prices (Moore and Lobell, 2014):

$$\max_{prod.\,pract.} V = p'_{outputs} f_{prod}(Meteo, Soil, Inputs, Variety) - p'_{inputs} Inputs + Subsidies, \quad (1)$$

where V is the value of agricultural activity, $Meteo$ is a vector of growing season meteorological variables, p_{Outputs} is a vector of output prices, p'_{Inputs} is a vector of input prices and $f_{\text{prod}}()$ is a vector of production functions. We assume that farmers have adjusted production practises in the long-run, maximising the value of agricultural activity given environment and policies. However, contrary to the underlying assumption of classical Ricardian studies (Mendelsohn and Massetti, 2017; Mendelsohn et al., 1994), we do not expect that farms are able to perfectly adjust their production practises to match climatic conditions. Given these conditions[1], we expect the individual outcome variable ($\bar{V}$) to only depend on exogenous variables within production functions of farms, variation in climate ($\bar{W}$) and a set of further controls, including soil and subsidies (Ξ):

$$\bar{V} = f_1(\bar{W}, \Xi). \quad (2)$$

The outcome $\bar{V}$ depicts the long-run value of agricultural activity depending on the climate a farm is facing. In this case, a farmer is expected to employ various adaptation measures using the acquired knowledge, while managing investments accordingly. We assume that the adaptive capacity of farms is uniform, meaning that information on climate is equally available and that each farm has the same access to resources and technologies. Therefore, each farm has the possibility to adapt likewise. This is contrary to a large-scaled framework

[1] We further assume that relative prices remain constant and that farmers are risk-averse.

such as Vanschoenwinkel et al. (2020), who suggest differences in resources, technologies or human capital throughout the European Union. However, our approach focuses on investigating the extent farms are able to adapt on average, given common barriers, rather than the effect of heterogeneous adaptive capacity. Therefore, we do not expect farms to adjust optimally to climate, due to a slow adaptation process, which may be influenced by lacking information or limited resources.

Still, observation of (im)perfect adaptation is far from being trivial. Facing a non-experimental situation, identification is quite complex since not only the value of agricultural activity changes with climatic conditions but adaptation too. As each farmer is expected to slowly adjust according to climate in the long-run, adaptation is determined by climate. Therefore, the observation of a farm encountering climate change but remaining at the same level of adaptation is impossible. To overcome this issue, we follow the work of Moore and Lobell (2014), who use the fact that farms are not only exposed to climate, but also to weather (W), which varies between years[2]. The value of agricultural activity in the short-run V can thus be expressed as a combination of an anticipated climate ($\bar{W}$) and a weather anomaly ($W - \bar{W}$):

$$V = \bar{V} + f_2(W - \bar{W}). \tag{3}$$

Relying on additional inter-annual weather variation represents a significant advantage within this framework. Farmers are assumed to slowly adjust to the climatic conditions they are facing, utilising the whole set of adaptation measures (long-run response). However, implementing long-term adjustment to unexpected weather conditions throughout the growing

[2]We solely account for weather fluctuations, as we expect soil not to vary between years and that changes in policy are fully known.

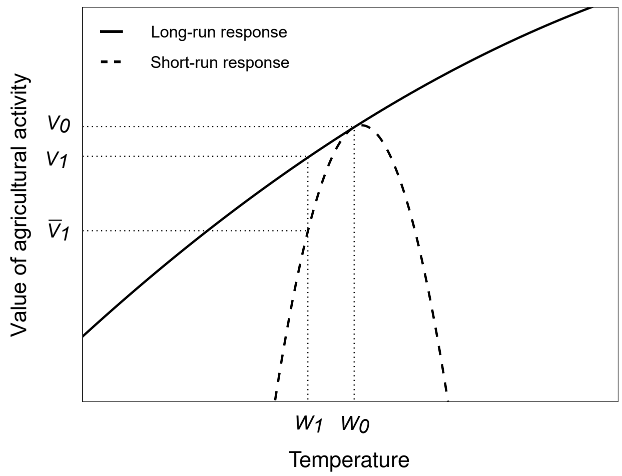
season is not possible (short-run response). Therefore, the different responses determine the value of agricultural activity capturing long-term adaptation that farmers are able to implement ($\bar{V}$) and the value of agricultural activity from an unanticipated weather, where adaptation cannot be employed and thus remains at the level of climate (V) (Moore and Lobell, 2014). Introducing weather variation thus allows us to identify and compare the value of agricultural activity given different levels of adaptation. Consequently, we expect two possible states of adaptation,

$$\text{where} \begin{cases} \text{farms are perfectly adapted} & \text{if} \quad \bar{V} > V \\ \text{farms are imperfectly adapted} & \text{if} \quad \bar{V} < V. \end{cases}$$

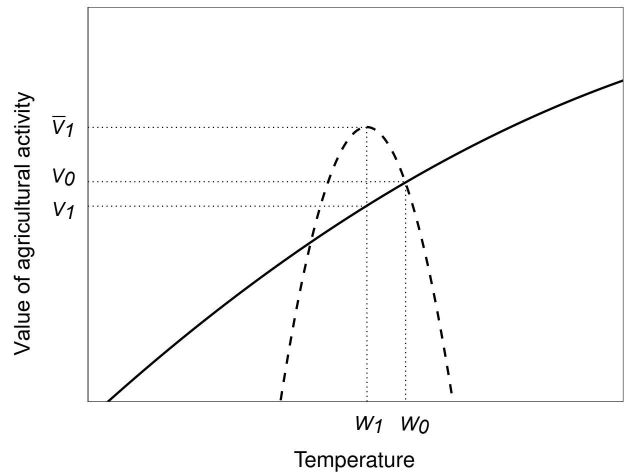
If each short-run response leads to a diminishing value of agricultural activity, perfect adaptation is implied. In this case, farmers optimally adjust to climate and can thus maximise the value of agricultural activity along the long-run response, while each other adaptation would lead to a decrease ($\bar{V} > V$). Conversely, imperfect adaptation exists, if short-run responses can lead to a higher value of agricultural activity than the long-run response. Farms along the long-run response could increase the value of agricultural activity and thus denote potential gains of adjusting accordingly ($\bar{V} < V$).[3]

The expected states of adaptation are further drawn in figure 1, in order to illustrate the extent of adaptation. The constant line represents a hypothetical long-run response of the value of agricultural activity to temperature, whereas the dashed line represents the

[3]Further, a special case can occur, where the value of agricultural activity for climate and weather conditions remain the same, denoted by equal short- and long-run responses ($\bar{V} = V$). Hence, farms are either not benefiting from long-term adaptation or not implementing any. However, we expect this case to have rather limited relevance in the present analysis.



(a) Perfect adaptation.



(b) Imperfect adaptation.

Figure 1: Diagrammatic illustration of the expected states of adaptation.

short-run response for weather.

Figure 1a depicts perfect adaptation, as the long-run response lies above the short-run response curve. Within this case no other adaptation than those to the anticipated, current climate yields a higher value of agricultural activity. For example, if the value of agricultural activity is V_0 at a climate W_0, a cooler weather W_1 would lead to a decrease to $\bar{V}_1$. However, if the cooler temperature was anticipated, the value of agricultural activity would only decrease to V_1. Therefore, the farm benefits from being adjusted accordingly ($V_1 > \bar{V}_1$) at temperature W_1. Consequently, perfect adaptation is present and the assumption of the Ricardian method holds. In other words, if perfect adaptation to climate is present, all short-run deviations in weather from a given climate lead to a decrease in the value of agricultural activity for farms.

However, farms have been exposed to continuous climate change over the last decades, with constantly increasing temperature (IPCC, 2014). Considering this, farms need to continuously adapt in order to keep up with climatic changes. Yet, as pointed out before, farms can face certain limitations to adjustment, potentially leading to a slow process of adaptation. Therefore, we expect that farms are not able to fully adapt to the climatic conditions they are facing but are lagging behind. Such a case is depicted in figure 1b, where a farm can achieve a higher value of agricultural activity than the observed long-run response would actually suggest. While the long-run value of agricultural activity is V_0 at a climate W_0, unexpected cooler weather W_1 would lead to an increase, with a short-run response optimum at $\bar{V}_1$. If we compare this with the long-run value of agricultural activity V_1, we find it to be lower ($V_1 < \bar{V}_1$). Therefore, this case indicates imperfect adaptation as farms could further increase their value of agricultural activity at a given temperature level by further adaptation. For example, a farm would need to have already adjusted to even warmer climatic conditions W_0 in order to get the highest attainable value of agricultural activity $\bar{V}_1$ at climatic conditions W_1. As the degree of imperfect adaptation is defined by the distance between the short-run optimum at W_1 and the corresponding climate W_0 at the x-axis, this difference can be interpreted as extent of adaptation.

2.2 Econometric estimation

The estimation of the model presented in the conceptual framework requires joint identification of short- and long-run responses, to adequately assess farm-level adaptation and its extent. Therefore, we take an econometric model using panel data, which relies on both, cross-sectional variation in climate and inter-annual variation in weather as a point of departure (Moore and Lobell, 2014):

$$V_{it} = \bar{W}_{it}\beta_1 + \bar{W}_{it}^2\beta_2 + D_{it}^2\beta_3 + \beta_4 X_{it} + \alpha_i + v_t + \varepsilon_{it}, \tag{4}$$

where V_{it} are the profits per hectare of farm i in year t, representing its value of agricultural activity. Meteorological variables are denoted by the long-term climate $\bar{W}_{it}$, its square form $\bar{W}_{it}^2$ and weather deviation $\bar{D}_{it}^2$ and contain a vector including growing season temperature and precipitation. Further, X_{it} is an additional control, α_i and v_t denote farm- and time-fixed effects, respectively, and ε_{it} represents a zero-mean error term.

Climate is represented by $\bar{W}_{it}$ and its squared form $\bar{W}_{it}^2$, which are both defined as 20-year moving averages of daily mean temperatures and precipitation sums over the growing season (March to September). Another possibility would be to simply use the long-term average of climate, resulting in the same if climate is stationary (Moore and Lobell, 2014). However, the assumption of stationary climate seems relatively restrictive, given the fact that there has been constant warming over the last decades (IPCC, 2014). Further, climate is defined as 20-year moving average in order to represent a typical long-term planning horizon of farmers, where long-lived capital investments are in place, and thus rate of adjustment is expected. Still, the choice of climate was tested, using the same specification with 15-year and 25-year averages, respectively, with no substantive change of results. Including a quadratic term has particularly twofold advantages when estimating climate responses: First, it is generally acknowledged that the relationship between agricultural outputs and climatic effects is non-linear (Schlenker and Roberts, 2009). Second, employing a quadratic term in a fixed-effects model partially reintroduces cross-sectional variation in the estimation process (Mérel and Gammans, 2018). Considering this, the long-run effect of a changed climate on profits can be estimated.

In contrast, inter-annual weather variation is identified by a deviation term, which depicts the absolute distance from weather to climate. The deviation variable $\bar{D}_{it}^2$ is calculated as a squared term of weather realization in year i, defined as mean over the growing season, subtracted by climate, which is again defined as 20-year moving average $(W_{it} - \bar{W}_{it})^2$. Yet, this original econometric framework proposed by Moore and Lobell (2014) imposes the assumption that farmers are perfectly adapted to climate. Hence, they presume this term to indicate the penalty associated with having a weather that is different than the expected weather (i.e. climate) they are adapted to.

However, the specification employed seems overly restrictive for two reasons: First, it assumes that the absolute distance between climate and the current weather determines the extent of the penalty and not the sign of the difference, as also pointed out by them. This assumption would only hold if the effect of having a weather which is e.g. one degree warmer or cooler has the same effect on agricultural profits. Given that changing climate is expected to have a non-linear effect on agriculture, assuming equal effects of different weather conditions might seem inappropriate. Second, using only the quadratic term of the absolute distance implies that the short-run response curve is a tangent to the long-run curve, always depicting perfect adaptation if an inverted U-shape is estimated. Thus, relying solely on the quadratic term inhibits the cases of imperfect adaptation, given the right sign of the coefficient, and the extent of adaptation cannot be identified. Although this specification might yield applicatory results, as it almost automatically imposes the assumption of perfect adaptation, we find it rather restrictive and forced. Given that we expect farm-level adjustments to differ from perfect adaptation, the original framework described is not suitable in this work and a more flexible specification is required. To fully account for those responses we extend the framework to a more flexible case, which can be expressed as:

$$\begin{aligned} V_{it} = {} & \bar{W}_{it}\beta_1 + \bar{W}_{it}^2\beta_2 + D_{it<0}\beta_3 + D_{it<0}^2\beta_4 + D_{it>0}\beta_5 + D_{it>0}^2\beta_6 + \\ & (\tau \times \bar{W}_{it})\beta_7 + \beta_8 X_{it} + \alpha_i + v_t + \varepsilon_{it}. \end{aligned} \tag{5}$$

In contrast to equation 4, where the deviation term is simply defined as the squared term of absolute distance between weather and climate, this specification is much more flexible. As described in figure 1, we expect imperfect adaptation, depicted by different effects of positive and negative weather deviations. Consequently, we split up the deviation term presented in equation 4, which allows us to identify the impacts from e.g. warmer and cooler temperature separately and thus the extent of adaptation. As we do not assume profits to be maximised at climatic conditions, contrary to Moore and Lobell (2014), we include both, a linear and squared term of weather deviation from climate, included in the vector τ. Further, in order to allow the short-run responses to vary with changing climate, we add interaction terms of climate and τ. Note, however, that our framework has the main advantage of not relying on any presumptions and thus still allows to capture perfect adaptation, if present.

Finally, X_{it} is an additional control variable, denoting received subsidies. Using subsidies allows to account for changes in the agricultural policy regime, as full policy information of farms is assumed. We further tested a specification with additional control variables[4] but decided not to include them as the regression might be confounded due to endogeneity concerns. Still, estimates of meteorological variables remain virtually unaffected by the different model specifications. In addition, farm fixed-effects α_i and time fixed-effects v_t are included, which capture (un)observed time-invariant and periodic heterogeneity, respectively. Using farm fixed-effects makes it possible to control for heterogeneity in farm characteristics such as size, production techniques etc., and geographical circumstances such as soil type, altitude and slope. Quddoos (2020) shows that omission bias in pooled OLS regression is evident and farm fixed-effects can efficiently control for time-invariant heterogeneity. To

[4] Further control variables include information on farm characteristics such as organic farming, farm area, rented land, family labour, livestock and arable land.

further consider factors affecting all farms equally, such as technological progress, price shocks or policies, time fixed-effects are employed. Time fixed-effects might be considered as reducing the magnitude of the coefficients from meteorological variables, in case they are similar throughout the study region. However, in the present study, influence of time fixed-effects seems of limited relevance, as considered regions denote a broad range of climate and weather conditions.

3 Data

We rely on two main sources to construct the final data set: Farm-level agricultural data is based on the European Union's 'Farm Accountancy Data Network' (FADN) and provided by the 'Federal Ministry of Agriculture, Regions and Tourism' (BMLRT). The data set is based on annual surveys of Austrian farms and accounts for a stratified sample of approximately 1% of total farms (BMLRT, 2020). Second, meteorological data are obtained from the Austrian governmental agency 'Zentralanstalt für Meteorologie und Geodynamik' (ZAMG). The data set employed is available in daily resolution and covers the whole area of Austria at a 1 x 1 km^2 grid (Hiebl and Frei, 2018; Hiebl and Frei, 2016). In the following the merged data sets are further explained.

Our dependent variable is farm profits per hectare, which is defined as the difference between revenues and costs, including subsidies received, and divided by the total farm area. Commonly, impact analysis studies using farm profits employ a logarithmic form (Bozzola et al., 2018; Reidsma et al., 2010; Deschênes and Greenstone, 2007). However, 48.91% of the farms in our sample denote losses, which inhibits log-transformation. Hence, reducing the sample to farms without economic losses might exclude farms which are most harmed by climate change. Consequently, it is our assertion that the omission of those farms would underestimate the impacts of climate change and yearly weather deviation. This would then lead to selection bias. In order to consider all observations, we thus follow Kurukulasuriya and Ajwad (2007) and use profits per hectare as dependent variable.

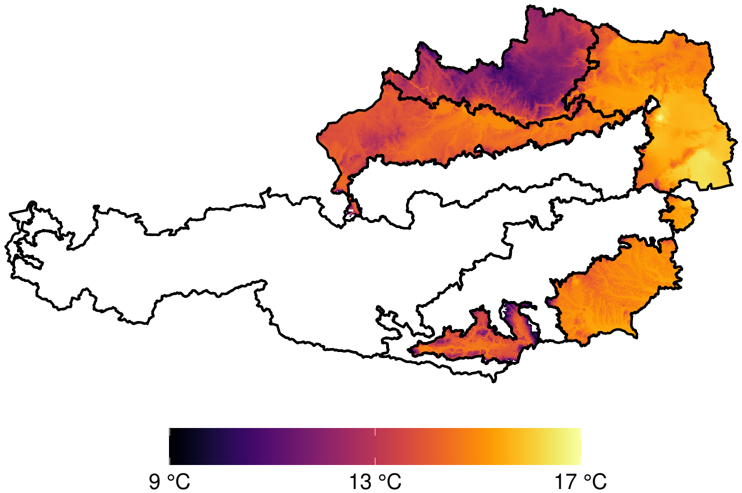
In order to account for changes in the agricultural policy regime, received subsidies per hectare are included as a control. Further, as relative prices are assumed to remain constant, we correct farm profits using an agricultural price index from 'Statistics Austria' (Statistics Austria, 2021). Table 1 presents the descriptive statistics. The mean profit per hectare amounts to 864.09 Euros per year and varies between -3,690.76 Euros and 11,242.77 Euros. Farm area ranges from 1.62 hectares to a maximum of 457.43 hectares, with an average of 44.09 hectares. Subsidies per hectare of farmland amount to an average of 484.03 Euros per hectare.

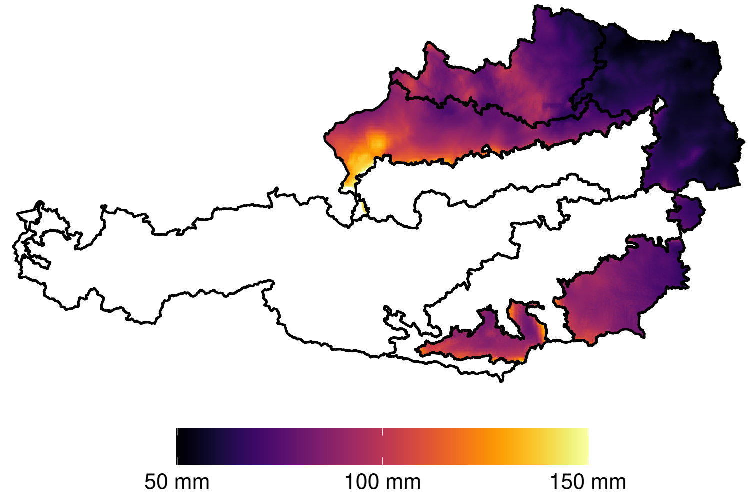
Table 1: Summary statistics of farm data and growing season meteorological data (2003-2016).

	Mean	Min	Max	Median	St. Dev.
Farm data					
Farm profit (€/ha)	864.09	−3,690.76	11,242.77	757.86	809.43
Farm area (ha)	44.09	1.62	457.43	38.24	29.03
Subsidy (€/ha)	484.03	0.00	2,609.67	473.26	173.01
Meteorological data					
Temperature: 20 years average (°C)	14.15	10.42	16.67	14.33	1.08
Temperature: weather deviation (°C)	0.49	−0.74	2.05	0.46	0.60
Precipitation: 20 years average (mm/month)	81.64	48.79	161.70	82.80	15.66
Precipitation: weather deviation (mm/month)	0.99	−54.36	49.13	1.78	15.74

The meteorological data comprises daily precipitation and minimum and maximum temperatures. It is available from 1961 to 2016 and considered throughout the growing season (March to September) for each year. Annual temperature values are derived from daily means of minimum and maximum values at each grid point. The variable depicting long-term temperature (i.e. climate) represents the rolling average over the past 20 years of growing seasons. Likewise, precipitation is defined as average monthly sums during the past 20 years. The observed cross-sectional variance of growing season climate variables between the location of farms is essential to derive the long-run effect of a changed climate on agricultural profits, considering adaptation. In contrast, the deviation is defined as difference between the past 20 years and current year. This term is sought to identify potential imperfect adaptation, as described in section 2. Meteorological data are calculated using the average of the four grid points closest to the farms. Detailed information on the distribution of meteorological data is provided in the lower panel of table 1 and in figure 2. The mean long-term temperature and precipitation are 14.15 °C and 81.64 mm/month, respectively. In the case of precipitation, high values of weather deviation can be observed, suggesting varying amount of rainfall throughout the years. The presence of exceptional rainfall events thus further underlines the importance of considering weather deviation in the regression framework. In contrast, the weather deviation of temperature indicates a relatively strong tendency towards a warming trend.

To illustrate the climatic conditions and past changes of meteorological variables in more detail, we plot the ZAMG grid for the sample regions of Austria in figure 2. Figure 2a and 2b represent the average climatic conditions of temperature and rainfall throughout the observation period. Both figures denote a large cross-sectional variance in climate: While north- and south-western regions still denote relatively cool climate, with values ranging from 9 °C to 14 °C, eastern regions are already encountering warmer conditions with temperatures up to 17 °C. In the case of precipitation we can observe some similarities, where north-eastern regions are rather dry with 50 mm/month, while western regions show higher levels of rainfall of up to 150 mm/month. Further, we plot the climatic trend of Austrian regions between 2003 and 2016 in figure 2c and 2d for temperature and rainfall, respectively. Precipitation

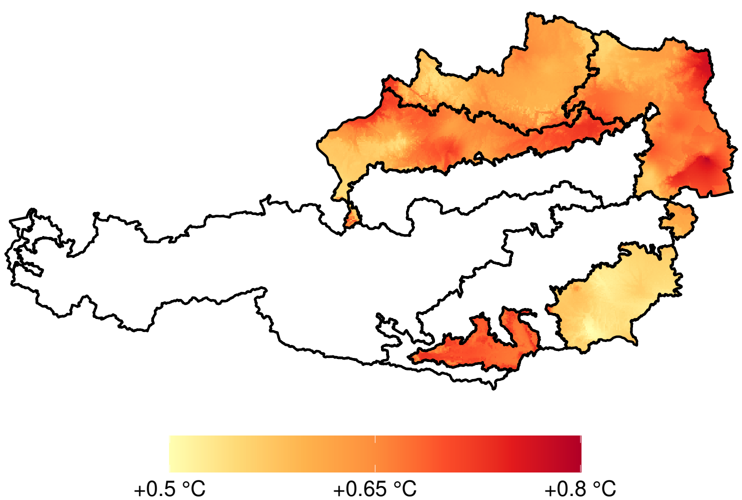


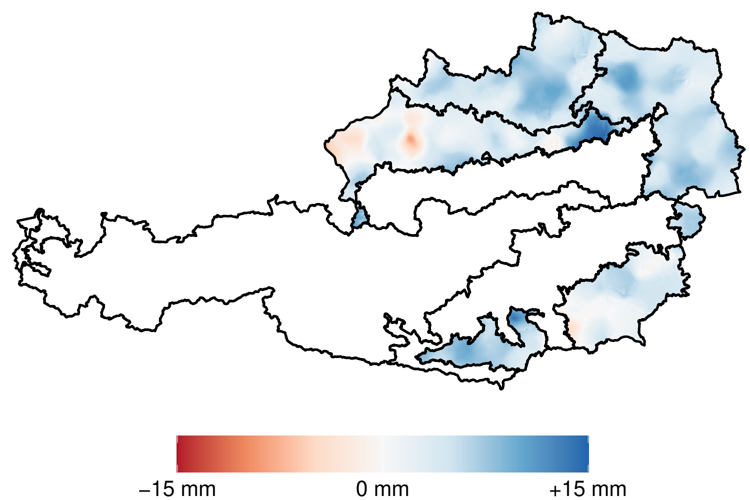


(a) Average climatic conditions of temperature.

(b) Average climatic conditions of precipitation.

Note: Some grid points within alpine mountain regions are omitted due to large deviation.





(c) Climatic trend of temperature.

(d) Climatic trend of precipitation.

Figure 2: Graphical representation of climatic conditions and trends within Austrian sample regions based on ZAMG (2003-2016).

shows partly diverging developments, with increasing amounts in most regions and little decrease within small areas in the north-west. In contrast, long-term temperature denotes a warming trend throughout Austria with an increase between 0.5 °C and 0.9 °C.

Recent works have shown that various farm types (Chatzopoulos and Lippert, 2015) or factors indicating different production, such as slope steepness (Quddoos, 2020), denote heterogeneous response to climate change. As Austrian agriculture is strongly influenced by geographic circumstances and thus embeds multiple historically evolved farm-types, this is an important issue to account for (Quddoos, 2020). Therefore, we employ the following strategy: First, the sample is reduced to continental regions in Austria. We rely on a subset of the whole Austrian sample, comprising typical production regions of arable farming[5], which are defined by natural land characteristics and farm characteristics (Wagner, 1991). Second, we restrict our sample to farms denoting at least once a minimum of one hectare arable land. Further, farms with a considerable amount (> 1 ha) of wine and fruit cultivation or horticulture are excluded, as these comprise highly specialised sectors, with a different set of adaptation options and thus potentially different responses. In this way, we still allow a wide range of possible adjustments to climate change, while restricting the sample to arable farms would implicitly impose the assumption of no change in production. Still, one might be concerned that dropping observations leads to insufficient variation in both, farms and meteorological variables. However, the farm characteristics presented in the upper section of table 1 show that the remaining farms are considerable diverse and thus allow capturing various adaptation. Regarding the latter, figure 2 demonstrates a broad range of climatic conditions throughout our study regions, which is comparable to previous work based on

[5]We use the major agricultural production areas Kärntner Becken, Südöstliches Flach- und Hügelland, Nordöstliches Flach- und Hügelland, Wald- und Mühlviertel and Alpenvorland

whole Austria (Quddoos, 2020).

The resulting data set of Austrian farms is an unbalanced panel as farms voluntary participate in the FADN sample (BMLRT, 2020). We assume that excluding both, farms entering and exiting the sample, leads to an information loss. While discontinued participation could be a sign of farm abandonment due to uneconomic farming (and thus climatic conditions), newly joining farms might provide information on adaptation. Still, we compare our preferred specification to an estimation using a balanced panel, showing little impact on the results. Finally, 0.5% of farms with highest and lowest deviation from their average farm profits are excluded, as these comprise unreasonably high fluctuation of profits, which cannot be explained by weather conditions. Consequently, the final data set includes the years from 2003 to 2016 and consists of 15,921 observations (1,137 on average per year). In total, 1,716 farms are included.

4 Results

Figure 3 provides a graphical representation of the estimated long- and short-run responses for temperature, based on equation 5. The red solid line denotes the long-run response to climate, whereas the black dotted line represents the short-run response to weather, given the climate corresponding to the point of intersection (drawn at the 25$^{\text{th}}$, 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles). To test the joint significance of meteorological variables Wald tests were conducted. We find all variables significantly different from zero except negative short-run precipitation deviations.

The long-run response denotes how profits evolve with changing climate, when farmers are able to (partially) adapt. In line with previous studies, the long-run response follows

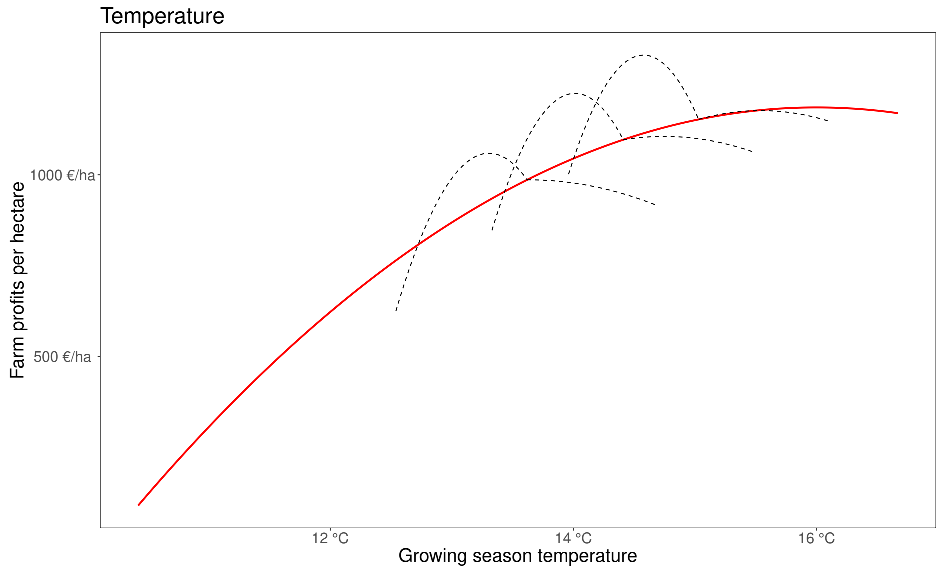


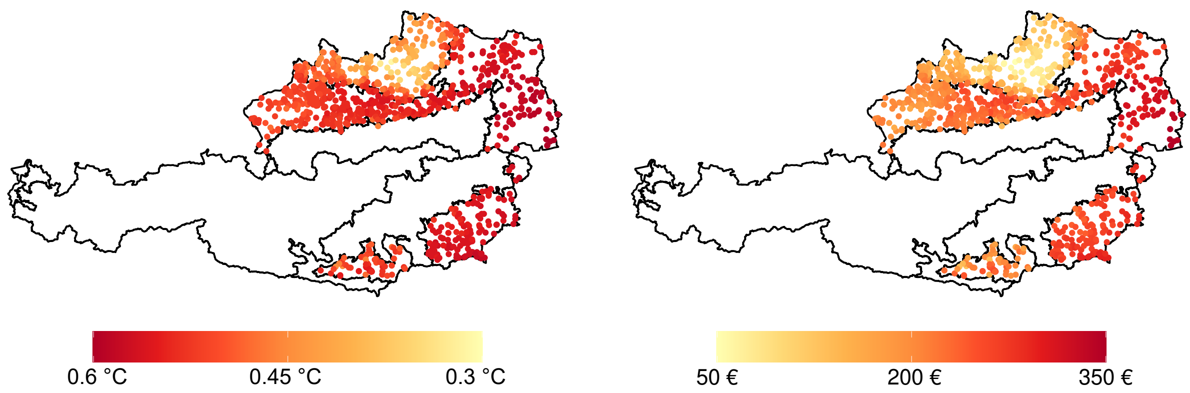
Figure 3: Grapical representation of the long-run (red solid line) and short-run (black dotted line) relationship between farm profits and temperature based on estimates of equation 5. The range of growing season temperature corresponds to our observations. Exemplary short-run response curves are drawn at the 25$^{\text{th}}$, 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of growing season climates and represent one standard deviation of climate.

an inverted U-shape, indicating increasing profits up to a certain point and declining profits afterwards (Moore and Lobell, 2014; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007). We estimate the maximum long-run response at a temperature of 16 °C and a precipitation of 144 mm/month. Compared to the study of Moore and Lobell (2014), covering 11 countries of Europe in a similar framework, these results are slightly below both, temperature (16.5 °C) and precipitation (162 mm/month). Considering the differences in study region and level of aggregation, we find our results substantively similar. With regards to future climate change, average marginal changes from the presented percentiles are calculated. Farms benefit from a warming of 1 °C with increasing profits of 81 Euros per ha, which amounts to 10.6% of the median. An increase of 10 mm/month in precipitation leads to higher farm profits of 150 Euros per ha, being equivalent to 19.7%. These results correspond to recent econometric studies in Europe, finding positive effects of increasing temperature and precipitation within this climatic range (Van Passel et al., 2017; Lippert et al., 2009)

Coming to the main objective of assessing the concept of perfect adaptation, the functional form representation of equation 5 allows us to separately assess positive and negative weather deviation, depicted in figure 3. In the case of cooler temperature than anticipated, the short-run responses lie clearly above the long-run response, denoting higher profits if temperature is lower than expected. The negative short-run response curves follow an inverted U-shape, representing positive effects of cooler weather up to a certain point, while above it decreases again. This is in line with our expectations of a short-run optimum above the long-run response, indicating imperfect adaptation.

As described in section 2.1, our framework makes it possible to determine imperfect adaptation. By defining the extent of adaptation as the difference between the current climate and the short-run induced optimum, the degree of lagging climate change adjustment is indicated. In addition, we simultaneously derive the potential gains of additional adjustment, defined as the difference between the profits of the estimated short-run optimum and the long-run profits at a certain temperature. At the median climate, farms are thus found to be lagging behind by 0.55 °C and denote potential gains of 213 Euros per ha. Further, the interaction terms between weather deviation and climate included in equation 5 allows us to assess how the short-run responses, and thus adaptation, vary with changing climate. We find both, the extent of adaptation as well as the potential gains of adjusting becoming more evident with warmer climate. While the gap amounts to 0.51 °C (168 Euros per ha) at the 25^{th} percentile, it increases up to 0.57 °C (250 Euros per ha) at the 75^{th} percentile.

For unforeseen warmer weather, we find mostly negative relationship with farm profits. Somehow surprisingly though, the negative effects of hotter weather decreases with warmer



(a) Extent of adaptation (°C). **(b)** Potential gains of additional adaptation (€/ha).

Figure 4: Spatial distribution of the difference between the current climate and estimated short-run optimum (extent of adaptation) of Austrian farms and potential gains of additional adaptation.

climate, indicating that higher temperatures than anticipated become less harmful to farms. One explanation might be that farms in warmer regions have already implemented certain heat-induced climate adaptation strategies. Therefore, they might be better prepared for reactions in the short-run too, and thus are better able to mitigate impacts from unforeseen weather to some extent.

In the case of precipitation, our findings suggest rather small impacts of weather deviation. The estimated short-run responses of precipitation denote slight negative effects. Further, the joint short-run coefficients of negative precipitation deviation are not statistically significant. Consequently, we find farm profits almost negligibly affected by unforeseen precipitation.

Using the coefficients of the temperature variables from equation 5, we further compute the extent of adaptation and the potential adaptation gains of Austrian farms for the last year (2016) of observational data. Figure 4 depicts the spatial distribution of both, resulting from climate heterogeneity within Austria (farm climate is based on different grid points).

In figure 4a, denoting the extent of adaptation, only little difference between regions can be observed. In most parts, farms are lagging behind around 0.55 °C, with a slightly lower extent of adaptation in the center and north-west (up to 0.3°C) and highest levels of 0.6 °C in the most eastern parts of Austria. Yet, with regards to potential gains of adjusting we find even stronger differences. According figure 4b, all Austrian farms could potentially gain by adapting according to the estimated optimum. While potential benefits of a shift in adjustments amounts to between 50-250 Euros per ha in north-western and southern regions, eastern regions denote potential gains of up to 350 Euros per ha.

5 Discussion

The present study set out to account for limitations of adaptation to climate change, in order to derive the extent of adaptation at the individual farm-level and potential gains of adjusting. Using Austria as study region we were able to demonstrate the following:

First, estimation results reveal that farms are not able to perfectly adjust to climatic conditions in the context of continuous climate change, as profitability at a given temperature level could be increased by adjusting according to warmer climatic conditions. We therefore conclude that adaptation to climate change of Austrian farms is lagging behind, which contradicts the assumption of perfect adaptation in classical Ricardian studies. Compared to previous empirical works (Burke and Emerick, 2016; Schlenker and Roberts, 2009), our joint framework further has the advantage of simultaneously assessing and quantifying imperfect adaptation. We determine actual climate adaptation is between 0.3 °C and 0.6 °C lower than the estimated optimum. We thus are able to show that the extent of adaptation varies with different reference climatic conditions of farms. While highest extent of adaptation is observed in warmest regions, farms located in moderate climatic regions of Austria are closer to perfect adaptation. A possible explanation might be that fewer effective adaptation strategies are available in warmer climates, as indicated by the negative relationship between high temperatures and long-run profits. Consider for example, that farms facing a moderate climate can mitigate impacts by implementing soil conservation or changing the variety of crops, which thus mostly requires rather basic knowledge and maybe only slight changes in machineries. However, if the warming continues up to a certain point, those measures might not be effective any more and farmers need to adjust more thoroughly by switching to different crops or even changing their production practises. Therefore, climatic conditions might be an additional limitation to farm-level adaptation. Consequently, farms with warmer climate might lack adjustments even more as adaptation effectiveness decreases with increasing temperature.

Yet, we observe meteorological differences, which might contribute to the results obtained: Corresponding to figures 4a and 2c, the regions with highest (lowest) extent of adaptation also show most (least) evident rise in temperature over the observation period. This would suggest that farms in warmer climates require even higher rates of adaptation, in order to keep up with climatic change. The observed difference between the warming trend in Austria broadly corresponds to the differences in the extent of adaptation, which would indicate offsetting effects. This would further contribute to the view of negligible differences in extent of adaptation. However, as this cannot be observed within all Austrian regions and some areas even show an opposite relationship, we still consider decreasing effectiveness of adaptation.

Second, if we further compare the results from figures 4a and 2c, we find the extent of adaptation is slightly below the corresponding warming trends in most of Austrian regions.

Hence, the difference may represent the increase of temperature farms able to compensate by implementing additional adaptation. This may suggest that farms can partly adjust to warmer climate. Consequently, adaptation at the farm-level would exist but implementation would be slower than assumed in Ricardian impact studies. This would also correspond to previous literature, acknowledging the processes needed to adapt to climate change (Vanschoenwinkel et al., 2016).

Third, our results provide further understanding of future climate change impacts and economic potential of farm-level adaptation. While long-run effects for the median temperature mostly suggest benefits, we find that farms facing this climate could further benefit by adjusting according to the estimated optimum. This becomes even more evident with warmer climatic conditions, as we find potential gains increase significantly. We thus can show that imperfect adjustment is linked to substantially higher potential gains in the warmest regions of Austria. Several studies have shown that agriculture is particularly vulnerable to heat (Lobell et al., 2013, Lobell, Bänziger et al., 2011), which might indicate that imperfect adaptation in warmest regions shows substantively higher impacts than in moderate climates. This further suggests that farms with already high temperatures are also under higher pressure to adjust accordingly. Shifting adaptation towards the estimated optimum thus might provide a significant potential of increasing farm profits. This further underlines the importance of climate change adaptation at the farm-level and thus calls for implementation of adequate adaptation measures. Consequently, it is important to identify most effective adaptation measures and further integrate and strengthen climate change adaptation.

Finally, it should be noted that the framework employed is not able to uncover all aspects of adaptation due to the 'black box' character of the Ricardian method (De Salvo et al., 2014). As the model implicitly accounts for both, adjustment and its limitations, identification of the effectiveness of adaptation measures and the main barriers of adaptation is not possible. For example, we cannot explicitly uncover the dynamic long-term adjustments costs due to various investments made. Hence, the relationship between potential gains and climate may correspond with higher adjustment costs due to the need for larger investments. Therefore, the costs associated with lagging adaptation might be overestimated. Consequently, more in-depth analyses of adaptation measures and drivers of adjustment are required to provide further understanding for climate change adaptation in the agriculture sector in Europe. However, information on adaptation measures and adaptive capacity is not easily available at the farm-level (i.e. awareness) and as recent literature emphasises, endogenous (Vanschoenwinkel et al., 2020; Chatzopoulos and Lippert, 2016).

6 Conclusion

Adaptation to climate change in agriculture has become a key goal within the European Union. Hence, many studies have sought to assess the impact of climate change, while accounting for potential adaptation. In particular, a widely used statistical method is the Ricardian method, following the relatively strict assumption of perfect adaptation. However, there is a upcoming evidence that adaptation to climate change is complex, with farms facing multiple limitations. Adjustment to climate change should thus be seen as a rather slow process over time. Therefore, this study set out to provide the first systematic account of farm-level adaptation in an econometric framework. Applying a panel data model which combines long-run climate data and short-run weather data allowed us to determine the extent of farm-level adaptation. Our results show that Austrian farms are lagging behind with adaptation to the climate they are facing. Although we find some evidence of adjustment, which indicates that farms actually implement adaptation, results suggest that farms still have significant potential to improve adaptation. Consequently, the concept of perfect adaptation does not hold within our framework, suggesting that at least in our study the Ricardian method underestimates the climate change adaptation potential. Based on our results, we conclude that agrarian policy should further provide and enhance programmes aiming at climate-specific adaptation measures. This is particularly important for regions with warmer climates, since our findings reveal in such regions higher degree of imperfect adaptation and a significant increase in potential benefits due to improved adjustments. However, this also suggests that potential benefits of catching-up on imperfect adaptation will become substantively higher with future climate change. In order to ensure the competitiveness of agricultural holdings throughout Europe, it is thus from utter importance to identify and further develop suitable and effective adaptation measures at the farm-level.

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A Annex

	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	112.78*	96.60	116.66	112.78*	205.12***	231.24***
	(65.09)	(62.51)	(84.25)	(65.09)	(60.39)	(68.97)
Temperature^2	−0.35**	−0.27	−0.36	−0.35**	−0.56***	−0.52***
	(0.17)	(0.17)	(0.22)	(0.17)	(0.17)	(0.16)
Dev. temperature (+)	−90.90**	−97.37***	−96.59**	−90.90**	−104.88***	−44.60
	(36.55)	(36.29)	(49.11)	(36.55)	(37.60)	(32.02)
Dev. temperature (+)^2	2.27	2.63	2.42	2.27	3.80	0.49
	(2.01)	(1.98)	(2.76)	(2.01)	(2.47)	(1.70)
Dev. temperature (−)	−258.47*	−282.31**	−373.25*	−258.47*	−170.12**	−325.64*
	(134.20)	(134.97)	(194.15)	(134.20)	(84.48)	(167.04)
Dev. temperature (−)^2	4.28	6.68	24.82	4.28	9.77	40.70
	(34.69)	(34.96)	(52.24)	(34.69)	(13.79)	(54.07)
Precipitation	320.40*	301.60*	456.49**	320.40*	202.63*	540.81***
	(174.16)	(169.35)	(217.12)	(174.16)	(112.49)	(189.35)
Precipitation ^{2}	−11.14	−11.00	−17.07	−11.14	−12.49*	−27.38**
	(10.59)	(10.46)	(13.43)	(10.59)	(6.87)	(11.28)
Dev. precipitation (+)	−46.59	−45.16	100.24	−46.59	−25.39	−5.12
	(69.02)	(68.22)	(101.48)	(69.02)	(74.44)	(68.15)
Dev. precipitation (+)^2	32.37	31.38	0.04	32.37	21.79	22.09
	(21.46)	(21.21)	(29.72)	(21.46)	(24.53)	(20.56)
Dev. precipitation (−)	74.25	76.36	240.84**	74.25	106.95	140.60*
	(73.76)	(71.74)	(116.73)	(73.76)	(71.54)	(76.74)
Dev. precipitation (−)^2	−9.48	−11.01	−40.71	−9.48	−16.35	−27.59
	(23.76)	(23.17)	(38.17)	(23.76)	(21.61)	(25.67)
Temperature × Temperature (+)	0.67**	0.69***	0.77**	0.67**	0.87***	0.25
	(0.26)	(0.26)	(0.36)	(0.26)	(0.27)	(0.23)

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Table A.1 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)
Temperature × Temperature $(+)^2$	-0.02	2.36^{***}	3.05^{**}	2.24^{**}	1.50^{***}	2.54^{**}
	(0.02)	(0.92)	(1.30)	(0.91)	(0.58)	(1.16)
Temperature × Temperature $(-)$	2.24^{**}	-0.02	-0.03	-0.02	-0.04^{**}	-0.004
	(0.91)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Temperature × Temperature $(-)^2$	-0.09	-0.10	-0.24	-0.09	-0.09	-0.33
	(0.24)	(0.24)	(0.35)	(0.24)	(0.09)	(0.37)
Precipitation × Precipitation $(+)$	1.02	0.95	-17.50	1.02	0.47	-5.07
	(8.70)	(8.61)	(12.46)	(8.70)	(9.18)	(8.78)
Precipitation × Precipitation $(+)^2$	-3.15	-11.85	-37.09^{***}	-12.14	-13.59^{*}	-20.61^{**}
	(2.76)	(7.95)	(13.05)	(8.22)	(7.99)	(8.86)
Precipitation × Precipitation $(-)$	-12.14	-3.02	0.89	-3.15	-2.43	-1.69
	(8.22)	(2.73)	(3.74)	(2.76)	(3.06)	(2.65)
Precipitation × Precipitation $(-)^2$	1.87	1.74	6.97^{*}	1.87	2.32	4.03
	(2.46)	(2.39)	(4.04)	(2.46)	(2.23)	(2.69)
Subsidies	0.76^{***}	0.73^{***}	0.61^{***}	0.76^{***}	0.77^{***}	0.76^{***}
	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.07)
Organic farming		153.84^{***}				
		(47.46)				
Farm area		0.19				
		(1.00)				
Rented land share		22.10				
		(125.08)				
Family labour share		225.78^{*}				
		(117.08)				
Livestock		349.19^{***}				
		(35.21)				
Arable share		177.91				
		(171.94)				

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Table A.1 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)
Observations	15,921	15,921	7,896	15,921	15,921	15,921
Adjusted R^2	0.68	0.69	0.67	0.68	0.68	0.68

Notes: Robust standard errors in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table A.1: Regression results denoting the relationship between farm profits and long-run changes in climate (temperature and precipitation) and short-run changes in weather: 1) Preferred specification: Mean climate is defined as a 20-year moving average, weather deviation is split up in negative and positive deviation and is allowed to vary with changing climate by including interaction terms (2) Additional farm characteristics are included (3) A balanced data set is used for estimation (4) Interaction terms between weather deviation and climate are excluded (5) Mean climate is defined as a 15-year moving average (6) Mean climate is defined as a 25-year moving average.