The impact of Climate Change on Farmland Prices: a Repeat-Ricardian analysis

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Abstract

Ricardian analyses of farmland values have become a cornerstone of the literature assessing the impacts of climate change on the value of agriculture. However, concerns about the lack of a formal econometric strategy to deal with omitted farmland characteristics have raised doubts about the identification of such impacts. This paper proposes an original method for estimating Ricardian models with plot fixed effects to control for confounding omitted variables. Specifically, we use plot-level repeat-sale data to investigate how differences in farmland prices are explained by differences in climate conditions between two sale dates in France from 1996 to 2019. We show that, in comparison to our repeat-Ricardian estimates, standard Ricardian analyses result in artificially low benefits of climate change. In particular, our repeat-Ricardian estimates indicate that hotter summers should benefit French agriculture, in complete opposition to our pooled Ricardian estimates or to the remainder of the literature. Our repeat-Ricardian results are robust to several specifications, length-definitions of climate and sub-samples. Our simulations suggest that the omitted variable bias in standard Ricardian analyses leads to an underestimation of the impacts of future climate changes of between 56% and 96%.

Keywords: Adaptation, Global warming, Hedonic pricing analysis, Panel econometrics, Repeat sales.

JEL Codes: Q12, Q53, Q54

1 Introduction

Climate change threatens the rise of agricultural yields and the profitability of the agricultural sector (Moore and Lobell, 2015). Farmers are however likely to adapt to such change. Mendelsohn et al. (1994) proposed a simple way to assess the costs of climate change borne by agriculture while taking into account farmers' adaptation: to regress land values (or land prices) on climate conditions. Indeed, because land prices reflect the discounted sum of future rents once all potential adaptation strategies have been implemented (e.g changes in capital or crop allocation), such regressions are supposed to provide the long-term value of climate for agriculture. Empirically, the so-called Ricardian analysis is a cross-sectional hedonic pricing analysis exploiting differences in farmland prices and climates across regions/farms. The Ricardian analysis has been applied in about fifty countries (Mendelsohn and Massetti, 2017), with consistent results across studies such as beneficial effects of hotter spring and autumn temperatures but harmful effects of hotter summer and winter temperatures (Massetti and Mendelsohn, 2011; Van Passel et al., 2017). However, concerns about the lack of ability to account for omitted variables in the Ricardian analysis has shed doubts on these estimates (Deschênes and Greenstone, 2007; Ortiz-Bobea, 2020). This weakness has led more recent studies to use panel econometrics (Blanc and Schlenker, 2017), regressing agricultural profits on weather conditions conditionally on individual and annual fixed effects. However, because weather fluctuations differ from real climate changes (Dell et al., 2014),[1] the literature considers that the panel approach only accounts for *short-term* adaptation, which leads to upward-biased estimates of the costs of climate change (Kolstad and Moore, 2020).

In this paper, we propose an original method for the estimation of Ricardian models. Using plot-level repeat-sale French data from 1996 to 2019, we investigate how differences in farmland prices across plots are explained by differences in climate conditions between two sale dates. Such a "repeat-Ricardian" analysis combines the advantages of both methods: to account for long-term adaptation thanks to the use of farmland prices (as in standard Ricardian analysis) while controlling for confounding omitted variables with individual (plot) fixed effects (as in the panel approach). Indeed, while previous Ricardian studies have implemented numerous control variables to limit potential omitted variable bias, the controls are usually not available at the plot level but rather at aggregated levels (in particular the municipal level in France), hiding the large remaining heterogeneity within the aggregation unit. This is particularly true for soil data, which are largely

[1] The difference between *climate* and *weather* arises from the distinction between a statistical distribution and a particular draw from this distribution: *weather* is a draw from the overall distribution summarized by *climate* (Dell et al., 2014). Accordingly, climate change corresponds to a change in the moments of the weather distribution.

heterogeneous even inside a municipality (Ay, 2021). Consequently, the inclusion of aggregated-level controls in previous studies does not necessarily overcome the omitted variable bias, and can even add measurement errors on top. Because most of these variables are however fixed over time, the inclusion of plot fixed effects in our repeat-Ricardian analysis is likely to provide the unbiased value of climate.

The source of identification of the value of climate in the repeat-Ricardian analysis is the exploitation of heterogeneous climate variations (as measured as changes of 30-year averages on seasonal temperatures and precipitation) over space. France has experienced such heterogeneous climate changes between 1996 and 2019: if some plots in our sample faced seasonal temperature reductions as large as -0.92°C, most plots experienced increases in seasonal temperatures, up to +1.47°C. As documented by the literature (e.g. Damania et al., 2020), changes in precipitation have been even more heterogeneous over space. The identification strategy in our repeat-Ricardian analysis thus does not solely rely on spatial heterogeneity in climate and land prices across regions/farms (as in the standard Ricardian analysis) but exploits together *time* and *spatial* heterogeneity. In other words, we do not use the typical "space for time substitution" identification strategy used by the Ricardian literature (if climate in 2050 in the North of France will be the same as the climate today in South of France, then farmland prices will be the same *ceteris paribus*) but rather identify the impacts of climate on farmland prices using exogenous variations in climate *conditionally on individual (plot) fixed effects*. Doing so, the repeat-Ricardian analysis share some similarities with the "long-differences" approach in climate econometrics (Dell et al., 2012), applied to crop yields by Burke and Emerick (2016) to capture the impacts of farmers' medium-term adaptation.

To illustrate the interest of our methodology, we estimate and compare standard pooled-Ricardian model with our repeat-Ricardian model on the set of French farmland plots that have been sold twice between 1996 and 2019. The data comes from the PERVAL database, provided by the French notarial agency. Usually used for fiscal purposes, this database compiles information on *all* real-estate asset transactions that have occurred in France since 1996 (including all houses, flats, forests, farmland, etc.). Taking the farmland plots that have been sold twice between 1996 and 2019 gives a sample of 4,307 plots (8,614 transactions). This sample provides several advantages. First, using observed transactions rather than self-reported values in hedonic analyses of farmland prices should provide more reliable estimates of the value of local amenities (Bigelow et al., 2020). Second, if aggregation bias can be important for cross-sectional Ricardian analyses (Fezzi and Bateman, 2015), it can be even more pronounced for panel analyses as aggregated panel data present composition issues. Third, these plots that have been sold twice have statistically similar price to the remainder of the plots sold over the same period. By exploiting repeat observed individual sales that are representative of the general farmland population, we believe that our study provides unbiased estimates of the impacts of climate change on French farmland values.

Using this sample, our repeat-Ricardian analysis suggests that climate change is likely to be less costly than previously estimated with pooled Ricardian models. In particular, our repeat-Ricardian analysis indicates that greater summer temperatures *increase* farmland prices. To our knowledge, such a result differs from the large bulk of the Ricardian literature, which has clearly concluded that summer temperatures have a negative impact on farmland values. Even in our sample, we find that standard pooled Ricardian estimates indicate that summer temperatures reduce farmland values. However, the positive impacts of summer temperatures in the repeat-Ricardian analysis are robust to several specifications and subsamples. The repeat-Ricardian estimates are in fact remarkably robust to the inclusion of control variables and changes in functional forms, which represents a sharp difference with standard Ricardian analyses (Schlenker et al., 2005; Deschênes and Greenstone, 2007; Ortiz-Bobea, 2020) and provides irrefutable proof of the remaining omitted variable bias in standard Ricardian estimates. Using the repeat-Ricardian estimates, our simulations suggest that climate change could increase French farmland values by between 54% and 203% by the end of the century (depending on the IPCC scenario used). Standard pooled Ricardian estimates suggest on the contrary that climate change will have no significant impact on French agriculture by the end of the century (irrespective of which scenario is used). Comparing the central estimated impacts of future climate changes with the pooled and repeat-Ricardian suggest that standard pooled Ricardian analyses underestimate by between 56% and 96% the positive impacts of climate change on French farmland values, illustrating the large omitted variable biases occurring in previous Ricardian analyses.

This paper contributes to two strands of the literature. First, we contribute to the Ricardian literature by introducing individual (plot) fixed effects. Doing so, we extend previous Ricardian estimations with panel econometric methods. Indeed, while the first Ricardian studies exploited cross-sectional differences across locations, more recent efforts have taken advantage of the panel structure of the data, notably with the estimation of pooled Ricardian models using either aggregated (Deschênes and Greenstone, 2007; Massetti and Mendelsohn, 2011; Schlenker et al., 2006) or individual data (Bozzola et al., 2018). Other studies have rather introduced random effects in the error terms in order to account for unobserved heterogeneity across farms/regions (Fezzi and Bateman, 2015; Vaitkeviciute et al., 2019). However, pooled and random effects approaches do not account for potential omitted variable bias linked to time-invariant factors. Only the use of individual fixed effects would remove such bias (Kuminoff et al., 2010; Wooldridge, 2015). To our knowledge, our study is the first to estimate Ricardian models with individual (plot) fixed effects. In line with Ortiz-Bobea (2020), we provide evidence that, despite the inclusion of (aggregated-level) control variables in Ricardian estimations, remaining omitted farmland characteristics lead to large bias in the assessment of the costs of climate change borne by agriculture.

Second, our repeat-Ricardian analysis relies on the utilisation of repeat sale data, that have never been used within the Ricardian framework. Indeed, the hedonic literature has shown that accounting for multiple sales of the same good over time allows the econometricians to control for most of the unobserved heterogeneity and, ultimately, to provide more efficient and unbiased estimates (Case and Quigley, 1991).[2] Because of the difficulty of setting up a panel of repeat-sales, such analyses are scarce in the literature. To our knowledge, Buck et al. (2014) is the single hedonic study using repeat farmland sales. Motivated by the measure of water value, Buck et al. show that previous cross-sectional and pooled analyses suffer from omitted variable bias despite the inclusion of numerous (aggregated-level) control variables. They show that the addition of plot fixed effects provides distinctly higher estimates than cross-sectional and pooled estimates. In this paper, we contribute to the literature by providing the first repeat-sales assessment of the value of climate.

The paper is structured as follows. We first present the theoretical and empirical framework of the repeat-Ricardian analysis. In addition to describing the data, Section 3 provides a spatio-temporal analysis of changes in both farmland prices and climate conditions across France. We present our repeat-Ricardian estimates in Section 4, and compare them with standard pooled Ricardian estimates. We also perform several robustness tests and heterogeneity analyses. In Section 5, we use our preferred estimates to run simulations using future climate conditions and assess the costs of climate change for French agriculture. We conclude in Section 6.

2 Methodology

The Ricardian analysis consists of a hedonic pricing analysis where farmland prices depend on a set of characteristics. Developed by Rosen (1974), the hedonic analysis postulates that, under competitive markets with fully available information, one can retrieve the value of any characteristic of interest (here, climate) of the considered good (here, farmland) by statistically explaining the

[2] For example, Chay and Greenstone (2005) show that estimating the first-differences of average counties' housing values by their first-differences of air quality over a decade provides theoretically consistent results (indicating that better air quality increases house prices), while equivalent cross-sectional analyses present some "perverse" signs (indicating that better air quality reduces house prices).

good's price by its characteristics. We give a theoretical presentation of the Ricardian model in Section 2.1 before turning to the econometric presentation of its estimation in Section 2.2.

2.1 The Ricardian framework

A potential risk-neutral buyer of a plot of farmland i observes the set of climate characteristics $\mathbf{C}_{it}$ and non-climate characteristics $\mathbf{N}_{it}$ that affect agricultural output in year t. The potential buyer knows that, by adding variable inputs x_{it} bought at global price p^x_t, they will produce quantities given by the production function $f(\mathbf{C}_{it}, \mathbf{N}_{it}, x_{it})$, assumed to be concave in x_{it}. Anticipating the value of these elements, the potential buyer can determine the stream of future annual rents that may be derived from i by solving:

$$\max_{\tilde{\mathbf{x}}_{it}} \Pi_{it} = \sum_{s=0}^{\infty} (E_t(p^y_{t+s}) f(E_t(\mathbf{C}_{it+s}), E_t(\mathbf{N}_{it+s}), x_{it+s}) - E_t(p^x_{t+s}) x_{it+s}) e^{-rs}, \tag{1}$$

where $E_t(p^y_{t+s})$ and $E_t(p^x_{t+s})$ are the buyer's anticipations of agricultural and input prices for year $t+s$ ($\forall s > 0$) in year t. Similarly, $E_t(\mathbf{C}_{it+j})$ and $E_t(\mathbf{N}_{it+s})$ are the anticipated characteristics of plot i for year $t+s$ ($\forall s > 0$) in t. The discount rate r is assumed to be constant. The solution of program (1) is the stream of optimal input applications over the horizon period. The corresponding Π^*_{it} represents the discounted sum of expected farmland rents across all time periods or, in other words, the expected net present value of the agricultural production from i in t.

The value of climate for plot i depends on the impacts of climate in equation (1). In particular, a change in climate conditions could affect the buyer's practices, ultimately affecting (i) agricultural production and thus (ii) the revenues and (iii) the costs of farming. The interest of the Ricardian analysis is that the econometrician does not need to observe all these elements but only the net present farmland value. Indeed, the cumulative long-term effects of climate correspond to the impacts of climate on Π^*_{it}. As an illustration, consider a temporary increase in temperature by +1°C in year t, which affects the contemporary economic rent – and thus the expected net present value – by λ. In this case, λ is the (shadow) value of one additional degree Celsius in t for i. A limit of the Ricardian analysis is that farmland rents and net present farmland values are not directly observable by the econometrician (or only through declarative surveys; see Bigelow et al., 2020).

Fortunately, the net present value of farmland Π^*_{it} is theoretically equal to the land price P^l_{it} in competitive land markets without any market power (Capozza and Helsley, 1989). Several studies suggest that, indeed, farmland is exchanged in well-functioning and competitive markets in the US (Just and Miranowski, 1993) and Europe (Ciaian and Kancs, 2012). Also, because farm size is small in western Europe (and in France in particular), it is common to assume no market power for farmers (Ciaian et al., 2010). In the following, we assume that the French farmland market is competitive and, consequently, we write:

$$P^l_{it} = \Pi^*_{it}. \tag{2}$$

This equivalence is convenient for econometricians as farmland prices can be observed.

Combining equations (1) and (2) allows us to retrieve the hedonic pricing function for farmland. Formally, the hedonic pricing function $h(.)$ links farmland prices and characteristics such that:

$$P^l_{it} = h(\mathbf{C}_{it}, E_t(\mathbf{C}_{it+1}), ..., E_t(\mathbf{C}_{it+\infty}), \mathbf{N}_{it}, E_t(\mathbf{N}_{it+1}), ..., E_t(\mathbf{N}_{it+\infty}), p^y_t, E_t(p^y_{t+1}), ..., E_t(p^y_{t+\infty}), p^x_t, E_t(p^x_{t+1}), ..., E_t(p^y_{x+\infty})).$$

Using such notations, the impact of a temporary additional degree Celsius in year t on plot i is equal to the partial derivative of $h(.)$ with respect to this temperature increase, which corresponds to λ. However, climate change cannot be interpreted as a temporary change in temperatures and precipitation but rather corresponds to a permanent shift of these variables.

As highlighted in equation (3), the value of a permanent shift in climate depends on the form of buyers' anticipations for the set of future farmland characteristics and prices. For a long time, Ricardian analyses have assumed myopic farmers with naive climate expectations (Mendelsohn et al., 1994; Massetti and Mendelsohn, 2011; Schlenker et al., 2005), i.e. with $E_t(\mathbf{C}_{it+s}) = \mathbf{C}_{it}$ ($\forall s \geq 0$). However, Severen et al. (2018) showed that, in 2007, US farmland values were already capitalizing the IPCC projections for the end-of-the-century climate. However, historic and future climates are highly correlated and the difference between the two increases with the considered time horizon (Masson-Delmotte et al., 2021). Hence, the differences between historic and future climatic conditions can be considered as small in the years following the sale date. Because our repeat-Ricardian analysis exploits short-term variations in climate (typically a decade or so, see Section 3), we assume that farmers have naive expectations of future climatic conditions.

The form of the expectations for the remaining drivers of farmland prices is the subject of greater consensus in the literature. Ricardian studies have usually assumed naive expectations for prices as well as for non-climate plot characteristics. This particularly applies to physical characteristics of farmlands such as topographic and soil conditions (Buck et al., 2014), which remain fixed over decades. However, other local non-agricultural drivers of farmland prices vary with time (Ortiz-Bobea, 2020). This is the case for population density (Plantinga et al., 2002), for which we assume farmers' naive expectations about future levels. Given these assumption about farmers' expectations, we can simplify the hedonic pricing function as follows:

$$P^l_{it} = h(\mathbf{C}_{it}, \mathbf{N}_{it}, p^y_t, p^x_t). \tag{4}$$

The hedonic pricing framework specifies that the value of any characteristic is equal to the partial derivative of $h(.)$ with respect to this characteristic. In particular, the value of a permanent increase of one degree Celsius after t (expressed as an increase of one degree for the zth element of $\mathbf{C}_{it}$, i.e. $\mathbf{C}^{(z)}_{it}$) is equal to:

$$\frac{\partial h(\mathbf{C}_{it}, \mathbf{N}_{it}, p^y_t, p^x_t)}{\partial \mathbf{C}^{(z)}_{it}} = \frac{\mathrm{d}P^l_{it}}{\mathrm{d}\mathbf{C}^{(z)}_{it}} = \frac{\mathrm{d}\Pi^*_{it}}{\mathrm{d}\mathbf{C}^{(z)}_{it}} = \sum_{s=0}^{\infty} \lambda e^{-rs}. \tag{5}$$

Under efficient land markets, the value of the partial derivative of the hedonic pricing function (4) with respect to temperature equals the discounted sum of shadow values of one degree Celsius λ over the considered time horizon. The aim of the Ricardian literature is typically to determine the value of the partial derivative in (5). Yet, this value depends on both the functional form of the hedonic pricing function (4) and the estimator used. We now present our econometric strategy.

2.2 The econometric strategy

Previous studies traditionally used cross-sectional variations in farmland prices and climates across locations for a single year to estimate Ricardian models (e.g. Mendelsohn et al., 1994; Schlenker et al., 2005; Severen et al., 2018). In order to reduce potential omitted variable issues, it is common practice to add a large set of farmland characteristics as controls. However, Deschênes and Greenstone (2007) showed that most Ricardian estimates were actually unstable over time when estimating successive cross-sectional Ricardian models for different years on identical geographical areas, even with the addition of a large number of control variables. According to Deschênes and Greenstone, this instability provided irrefutable proof of the detrimental role of omitted variables in cross-sectional Ricardian studies. Consequently, Massetti and Mendelsohn (2011) proposed that Ricardian models be estimated from panel data. They show that, when time-varying variables and time fixed effects were included together in a pooled model, Ricardian estimates were in fact robust over time. Due to the (quasi-)panel dimension of our data (see Section 3), we adopt the pooled approach as a benchmark.

Pooled Ricardian model. A pooled Ricardian model can be written as:

$$\log(P^l_{ijt}) = \alpha + \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\beta}'\mathbf{N}_i + \boldsymbol{\gamma}'\mathbf{N}_j + \boldsymbol{\delta}'\mathbf{N}_{jt} + \epsilon_{ijt}, \tag{6}$$

where P^l_{ijt} is the price of plot i in municipality j in year t, $\mathbf{C}_{jt}$ is the vector of climate variables in municipality j and year t, $\mathbf{N}_i$ is the vector of plot i's observed time-invariant characteristics (plot size here), $\mathbf{N}_j$ is the vector of the observed time-invariant characteristics of the municipality j where i is located (here, average altitude, slope and soil conditions) and $\mathbf{N}_{jt}$ is the vector of time-varying variables (here, population density) for municipality j in year t. The set $(\alpha, \boldsymbol{\theta}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta})$ contains the parameters to be estimated.

We consider four types of pooled Ricardian model: (i) model 1 defined as equation (6) without any control variables where the error terms ϵ_{ijt} are assumed to present white noise properties, (ii) model 2 defined as model 1 but with the inclusion of the commonly used control variables $\mathbf{N}_i$, $\mathbf{N}_j$ and $\mathbf{N}_{jt}$, (iii) model 3 defined as model 1 but with annual dummies such that the error terms are split into annual dummies (written η_t) and remaining idiosyncratic errors μ_{ijt} (i.e. $\epsilon_{ijt} = \eta_t + \mu_{ijt}$) and (iv) model 4 defined as model 3 but with the inclusion of the commonly-used control variables. In models 3 and 4, the annual dummies capture all annual common shocks affecting farmland prices. In particular, annual dummies capture the effects of commodity prices p^y_t and p^x_t (see equation (1)), financial shocks and changes in agricultural policies (that could be capitalized in farmland prices). Model 4, which includes both these annual dummies and the control variables, is likely to outperform the other three models (Massetti and Mendelsohn, 2011). In all cases, the pooled Ricardian models are estimated using ordinary least squares (OLS).

Repeat-Ricardian model. Despite the efforts to reduce potential omitted variable biases in previous Ricardian studies, the nature of agricultural and transaction databases prevents the inclusion of all the relevant farmland price drivers. In particular, several of the most important drivers of farmland prices are not measured at the plot level. This is the case of soil quality (i.e. the type of soils – limestone, clay or sand – but also grain sizes and soil depths), altitude and slope for example, whose values are typically available at the municipal scale. Soil quality remains, however, very heterogeneous within a municipality (Ay, 2021). Consequently, the inclusion of municipal measures of such characteristics (in $\mathbf{N}_j$) do not overcome the omitted variable biases and can even result in additional measurement error (Auffhammer et al., 2013). Fortunately, these characteristics (soil quality, altitude and slope) are fixed over time (Druckenmiller and Hsiang, 2019). The inclusion of plot fixed effects would thus remove the omitted variable biases due to these time-invariant but location-varying factors.

A Ricardian model with plot fixed effects can be written as:

$$\log(P_{ijt}^{l}) = \alpha + \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\beta}'\mathbf{N}_{i} + \boldsymbol{\gamma}'\mathbf{N}_{j} + \boldsymbol{\delta}'\mathbf{N}_{jt} + FE_{i} + \zeta_{ijt}, \tag{7}$$

where FE_i are the plot fixed effects that capture all the time-invariant unobserved factors of plot i. The introduction of plot fixed effects also capture all the time-invariant controls that are usually introduced in the Ricardian analyses, either at the plot ($\mathbf{N}_i$) or municipal scale ($\mathbf{N}_j$). Our repeat-Ricardian analysis consists of removing these time-invariant factors by estimating:

$$\log(P_{ijt}^{l}) = \boldsymbol{\theta}'\mathbf{C}_{jt} + \boldsymbol{\delta}'\mathbf{N}_{jt} + FE_{i} + \zeta_{ijt}, \tag{8}$$

where ζ_{ijt} are the error terms. Specifically, we estimate equation (8) using the within transformation, which allows us to conserve a large number of degree of freedom while taking into account for the individual time-invariant characteristics of the plots in our repeat sale sample. We thus estimate the Ricardian parameters using variations in both land prices and climates between the two sales dates. Doing so, we remove from all time invariant characteristics that may be correlated with long-term value of climate.

We consider four types of repeat-Ricardian models: (i) model 1 defined as equation (8) but without any control variables where the error terms ζ_{ijt} are assumed to present white noise properties, (ii) model 2 defined as model 1 with the addition of commonly-used control variables $\mathbf{N}_{jt}$ (i.e. municipal density here), (iii) model 3 defined without control variables but including annual dummies such that the error terms ζ_{ijt} are split into annual dummies (with η_t equals to one if the plot has been sold in t and zero otherwise) and remaining idiosyncratic errors ξ_{ijt} and (iv) model 4 defined as model 3 with the addition of the commonly-used control variables.

Our empirical strategy consists of estimating the different versions of the pooled Ricardian and repeat-Ricardian models (equations (6) and (8) respectively) on the set of French plots that have been sold twice between 1996 and 2019, and comparing the obtained estimates.

3 Heterogeneous changes in climate and price across France

The identification strategy of the repeat-Ricardian analysis relies on the exploitation of heterogeneous long-term changes in both climate and land prices across France. In this section, we investigate how climate and land prices have changed during the sample period (1996-2019).

3.1 Climate Changes in France

Measurement of climate variables represents an important empirical challenge in the Ricardian literature. A common practice in the literature is to include long-term average temperatures and precipitation for the four seasons (Mendelsohn and Massetti, 2017). While some studies have also examined the role of cumulative degree days over the growing season in addition to the four-seasons Ricardian model (e.g. Schlenker et al., 2006; Severen et al., 2018; Ortiz-Bobea, 2020), four-seasons Ricardian models have been identified as being superior to degree-days Ricardian models (Massetti et al., 2016) or two-seasons Ricardian models (Vaitkeviciute et al., 2019). Indeed, as degree days and average temperatures during spring and summer are almost perfectly correlated (Massetti et al., 2016), degree-days Ricardian models do not provide any substantial additional information. They actually even reduce the quality of out-of-sample predictions (Massetti et al., 2016). Also, because the effect of temperature is not the same in each season, aggregating temperatures over the growing season misses the consequences of unequal future seasonal changes. It also misses the consequences of climate change outside the growing season. This is particularly true for France, where most of the agricultural area is already planted in autumn and winter (such that autumn and winter temperature and precipitation may affect a large share of French agriculture).[3]

In line with the majority of the literature, we thus measure climatologies as seasonal long-term averages of temperatures and precipitation, where spring temperatures and precipitation are expressed in °C/day and cm/month respectively using averages over March-May (respectively June-August, September-November and December-February for summer, autumn and winter climatologies). More specifically, we compute the climatologies as 30-year averages of temperatures and precipitation between $t-30$ and $t-1$, i.e. climate in 1996 (resp. 2019) is measured as the averages of annual weather conditions between 1966 and 1995 (resp. between 1989 and 2018).[4]

[3]Spring crops (e.g. rapeseed or spring wheat) *only* represented 20% of the French useful agricultural area (UAA) in 2010. By comparison, winter crops (e.g. winter wheat and barley) occupied about 25% of the French UAA at that time (Lerbourg, 2012). Similarly, permanent crops (fruits and vineyards) and grasslands occupied together 33% of the French UAA in 2010 (Lerbourg, 2012).

[4]The heterogeneity of the climatologies for our initial and final periods thus relies on 23 years, 1989-1995 being common to the two periods. Such overlapping issues are further exacerbated in the econometric analysis. Indeed,

For this purpose, we use the daily weather information for the 8,604 French stations since 1959 from the SAFRAN database (provided by *Météo France*), which are already spatizalied at the 8×8 km^2 SAFRAN grid squares (9,892 grid squares for the whole France). We then downscale the climatologies from SAFRAN grid square level to the municipal level using the `meteoRIT` package in R (Desjeux, 2019).[5]

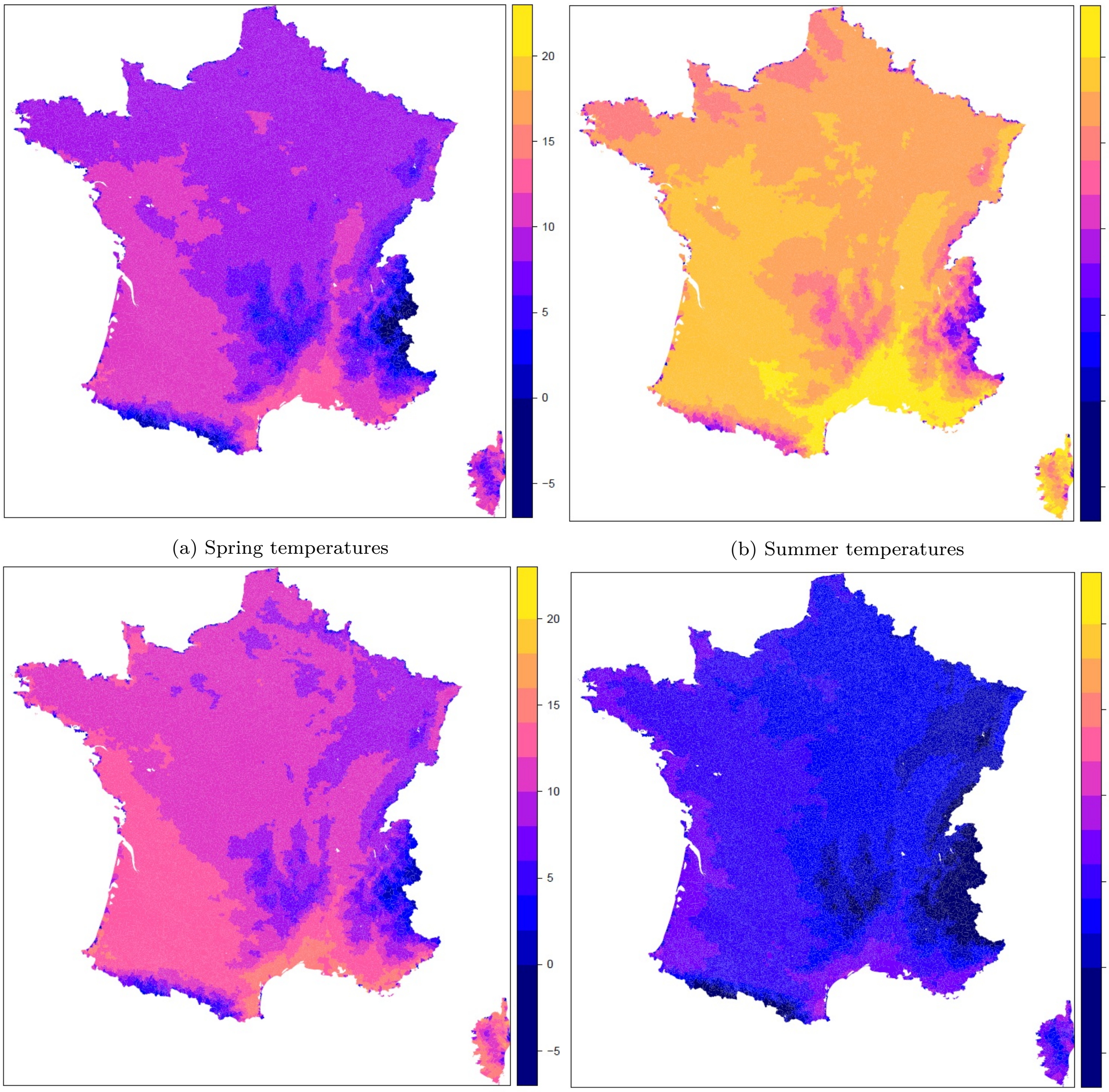
Climate in 1996. Figure 1 (resp. Figure A1 in the Appendices) presents the seasonal temperatures (resp. precipitation) for the 36,486 French municipalities over the period 1966-1995. These figures underline the great heterogeneity of climate in 1996. For example, the Mediterranean basin presents the highest temperatures in all seasons. Mountain areas in the Alps, the Pyrenees, the Massif Central and, to a lesser extent, the Jura display low temperatures during the whole year. The remainder of France presents rather similar 30-year temperature averages. However, the Atlantic coast benefits from higher precipitation in spring, autumn and winter than the central and eastern part of France (Figure A1).

On the basis of these characteristics, climatologists consider that France has four contrasted climates (Joly et al., 2010): Continental, Oceanic, Mediterranean and Mountain (see Figure A2 in the Appendices for the spatial distribution of the four climates in France). The Continental climate is the most widespread, characterized by high annual thermal amplitude and mainly located in north-eastern France. The Oceanic climate is located all around the Atlantic and Channel coasts. It has mild winters associated with cool summers and presents frequent rainfall throughout the year. The Mediterranean climate is the hottest in France, with irregular rainfall throughout the year and frequent droughts during the summer. The Mountain climate concerns those departments in and around the Alps, Pyrenees, Massif Central and Jura. It is characterized by cold winters and cool, wet summers.

Climate change between 1996 and 2019. Figure 2 presents evidences of spatially heterogeneous climate changes across France by showing changes in seasonal temperatures between 1996 and 2019. Over the whole of France, spring and summer temperatures increased by about 1.0°C on average, while autumn and winter temperatures showed a smaller increase of about 0.4°C (see Table A1 in the Appendices for detailed statistics on climate change in France). In particular,

given that the average length between two sales is 6.5 years (see Section 3.2), the heterogeneity of the differences in climate is driven by deviations on about a fifth of the 30-year averages.

[5]There are 36,486 municipalities in France, such that one weather station covers about 4 municipalities on average. The `meteoRIT` package proceeds to the downscaling using weights resulting from the GIS crossings of areas between the SAFRAN grid squares and the French municipalities.



(a) Spring temperatures

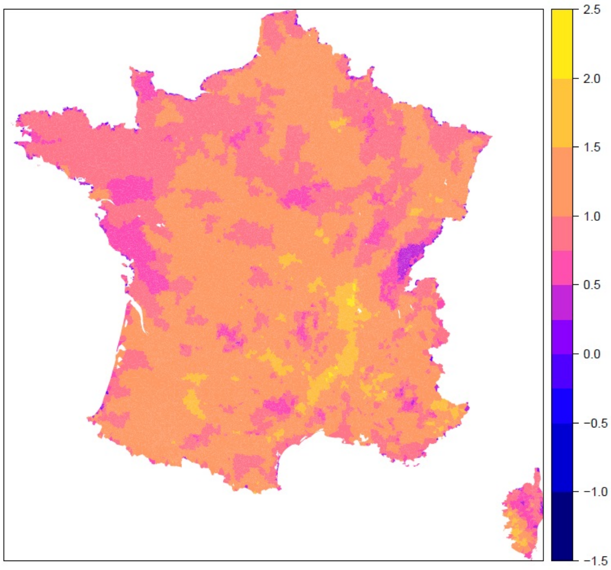
(b) Summer temperatures

(c) Autumn temperatures

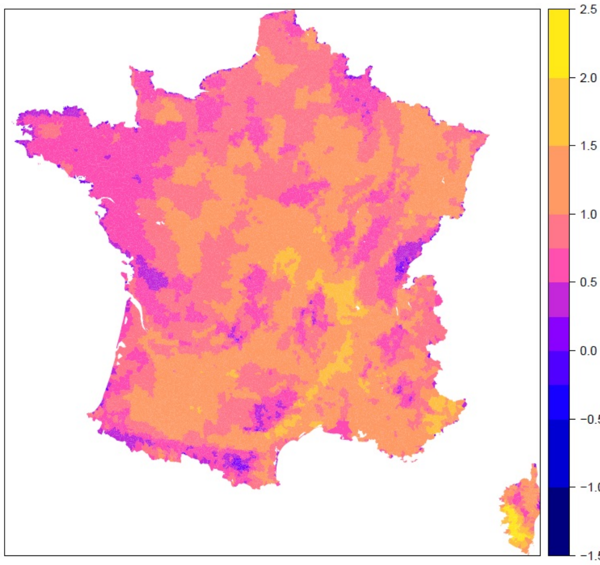
(d) Winter temperatures

Figure 1: Seasonal temperatures for the 1966-1995 period in France. *The information is expressed in °C/day and available for the 36,486 French municipalities. Spring temperatures are computed as the average of daily temperatures in March-May (respectively June-August, September-November and December-February for summer, autumn and winter).*

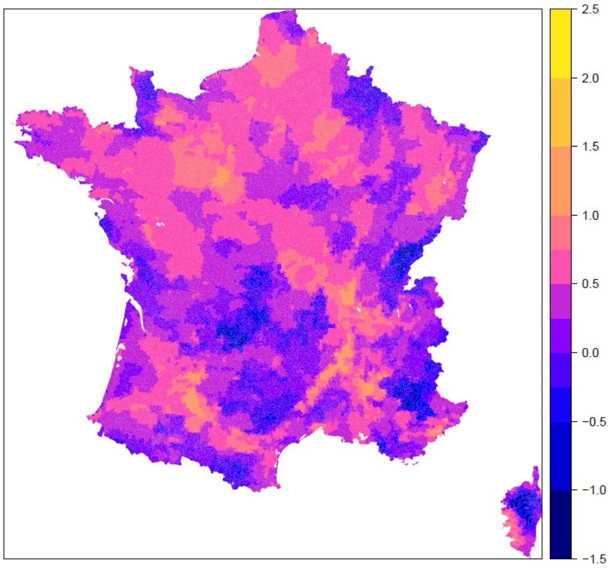
none of the municipalities showed a cooling of temperatures in spring or summer between 1996 and 2019 but about 30% of the municipalities showed a decrease in autumn and winter temperatures over the same period (Table A1). The greatest increases in spring and summer temperatures are mainly concentrated around south-eastern France (Figure 2). The increases in autumn and winter temperatures, though more homogeneous across France, are concentrated in the north of France and the *Rhone* valley.



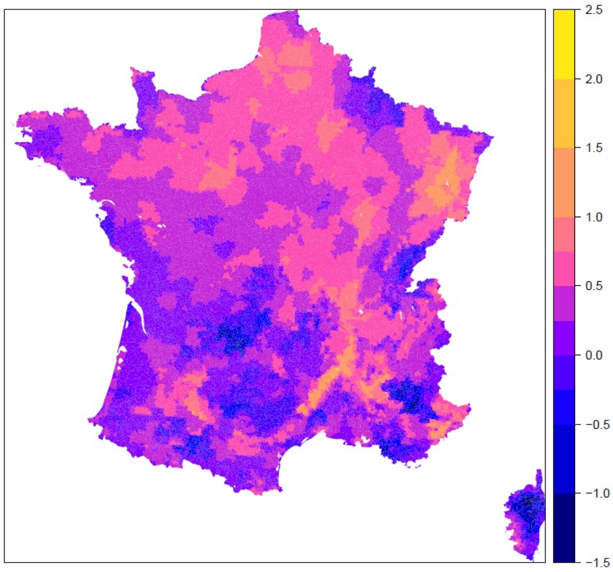
(a) Spring temperatures



(b) Summer temperatures



(c) Autumn temperatures



(d) Winter temperatures

Figure 2: Changes in seasonal temperatures from 1996 (1966-1995 averages) to 2019 (1989-2018 averages) in France. *The information is expressed in °C/day and available for the 36,486 French municipalities. Spring temperatures are computed as the average of daily temperatures in March-May (respectively June-August, September-November and December-February for summer, autumn and winter).*

During the period, precipitation increased in summer, autumn and winter by about 3.2%, 3.7% and 0.4% respectively but decreased by -1.1% in spring (Table A1). Precipitation changes are even more spatially heterogeneous than temperature changes (Figure A3 in the Appendices). While most regions suffer from a loss of spring precipitation, central France benefits from greater spring precipitation. The increase in summer and winter precipitation mainly occurred in the northern half of France. The increase in autumn precipitation is concentrated around the Mediterranean sea.

Overall, there have thus been heterogeneous climate changes across France, in terms of both temperature and precipitation. We exploit these sources of heterogeneity to identify the value of climate for agriculture in the repeat-Ricardian analysis.

3.2 Changes in land prices

We use information on individual farmland transactions from the PERVAL database. Provided by ADNOV (a company affiliated to the French notaries), the PERVAL database provides exhaustive information about all real estate transactions that have occurred in France (except for the *Ile de France* region) since 1996, distinguishing between houses, flats, farmland and forests. The information includes prices, property characteristics, location at the municipality level and transaction date. Over the 1996-2019 period, there were 660,755 transactions relating to farmland plots.

For the purpose of our repeat-Ricardian analysis, we purchased the sample of French plots that have been sold *exactly* twice between 1996 and 2019 and that maintained a similar area between the two sale dates.[6] This represents 4,494 plots over the whole of France (i.e. 8,988 transactions or 1.36% of all French farmland plots that were sold during our study period). Removing all transactions from Corsica and overseas departments leads to a sample of 4,395 plots (8,790 transactions). We then eliminated outliers based on plot size,[7] plot price,[8] and annual price variation.[9] Our final sample consists of 4,307 observations (8,614 transactions).

Table 1 presents the summary statistics of farmland transactions in our repeat-sale sample and in the general population and provides the *t*-value of the Student test comparing the variables in the two samples.[10] We use these tests to verify whether the repeat-sale sample is statistically equal to the general population. First, Table 1 indicates that the repeat-sale sample consists of plots that are on average smaller by 0.24 ha than the general population (i.e. 7.40% smaller).

[6] We do not access to the plots that have been sold more than three times between 1996 and 2019. This corresponds to 421 plots that have been sold three times in the time period, 15 plots that have been sold four times and one plot that has been sold five times.

[7] We drop the 0.5% smallest and the 0.5% largest plots.

[8] All prices are converted to 1996 euros and include taxes. We drop the 23 plots with a null price (for at least one transaction), which likely represent donations. Using the Z-score outlier detection procedure, we drop the eight plots for which the logarithm of the price (expressed in €/ha) for one transaction is higher than the upper outer bound (higher than the third quartile plus three times the interquartile range).

[9] We drop the 0.5% of plots presenting the largest negative price variation (expressed in %/year) and the 0.5% of plots presenting the highest price variations.

[10] We obtained the descriptive statistics on the full sample from ADNOV. We have no access to individual observations that have been sold only twice between 1996 and 2019.

Though small,[11] this difference is statistically significant at the 1% level. Buck et al. (2014) also reported that their repeat-sale sample was made up of smaller plots than the general population, even if the difference was not significant in their case. Second, the plot prices between the two samples are statistically equal. Despite the fact that the plots in the repeat-sales sample are on average sold at a lower price (in €/ha) than the general population, the *t*-value indicates that the difference is not statistically significant. This is an important difference from Buck et al. (2014), whose repeat-sale sample plots were sold at a significantly lower price than the general population. By comparison, even though our repeat-sale sample plots are marginally smaller than those of the general population, they are sold at similar prices. Third, Figure A4 (in the Appendices) shows that the spatial distribution of the transactions is similar between our repeat-sale sample and the general population. Overall, we thus consider that the plots that have been sold twice between 1996 and 2019 are statistically identical to the general population of all the transactions that occurred during the same period. Our estimates are thus likely to be representative of the costs of climate change on French agriculture.

Table 1: Summary statistics on transactions for the repeat-sales sample and the general population

	Repeat-sales (N=8,614)			All sales (N=660,755)			
	Mean	S.D.	Median	Mean	S.D.	Median	*t*-value
Area (ha)	2.99	4.79	1.29	3.23	7.36	1.02	3.02 ***
Price (€)	14,130	23,007	6,238	14,025	50,760	5,000	0.59
Price (€/ha)	9,133	16,506	4,214	10,434	16,366	3,278	0.74
Annual price variation (%/year)	15.76	39.53	4.74	-	-	-	-
Years between two sales	6.58	5.43	5.00	-	-	-	-

*Prices are expressed in 1996 real prices. Annual price variation represents the farmland price variation between the two sale dates. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01 respectively.*

Table 1 also displays the summary statistics on the length of time between the two sale dates and the corresponding annual change in farmland prices for the repeat-sale sample. We find that the sample consists of plots for which the median increase in prices is 4.74%/year, with a high level of heterogeneity. This is also highlighted in Figure 3: while some regions present rather homogeneous changes between 0% and 30% per year (e.g. south-western and central France), most regions present highly heterogeneous price changes between the two sale dates. For example, Brittany experienced both extreme negative and positive price changes. Overall, plots that showed a decrease in price are mainly located in the north-west of France and in the Paris basin. The east of France and the Mediterranean basin have a higher density of plots with high price increases.

[11] The small difference in farmland area between the two samples is also highlighted by the fact that the median plot size of the repeat-sale sample is actually *larger* than those of the general population.

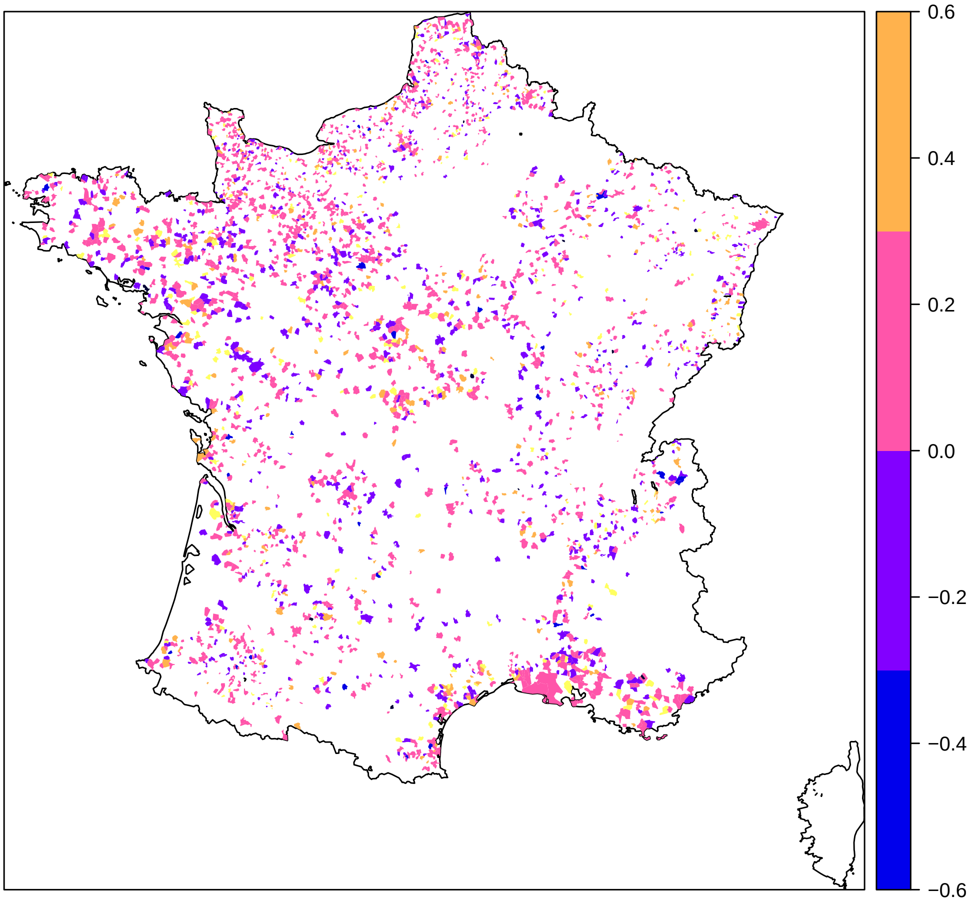


Figure 3: Annual price variation between the two sale dates. *Information expresses the variation rate of farmland prices between the two sale dates, using the price of the first transaction as the denominator. Annual variation rates are displayed at the municipal level for the 3,354 municipalities with at least one repeat sale. Among them, 953 municipalities experienced two repeat sale observations. In these cases, we show the average of the annual price variation within the municipality.*

This second spatial analysis of the heterogeneity of price changes throughout France between two sale dates reveals a diversity of situations, where some plots lose value over time, while most gain value over time. Our repeat-Ricardian analysis consists of explaining the drivers of these heterogeneous changes by the heterogeneous climate change between the two sale dates. However, as shown in Table 1, the mean period between two sales is rather short (6.58 years). Table A2 and Figure A5 (in the Appendices) indicate in particular that 52.47% (resp. 24.01% and 23.52%) of the plots making up our sample were sold for the second time after less than 5 years (resp. between 6 and 10 years and between 11 and 23 years). Our identification strategy (presented in Section 2.2) thus relies on climate changes over shorter time periods than those presented in Section 3.1. The following section presents the summary statistics of our sample.

3.3 Summary statistics

Given the sample construction described in Section 3.2, our sample consists of 4,307 farmland plots sold twice between 1996 and 2019 (8,614 observations). We link these observations to those of 30-year moving averages of climatologies at the municipal level. Data on municipal population density come from the French Institute of Statistics (*INSEE*). Data on soil texture conditions (four levels) were provided by the Joint Research Centre (Panagos et al., 2012) at a scale of 1:1,000,000 and further aggregated at municipal level.[12] Relief data (altitude and slope) are derived from the digital elevation model GTOPO,[13] available at the scale of 30 arc seconds (approximately 1km) and further aggregated at municipal level.[14] Table 2 presents the summary statistics of the variables in our sample (in terms of absolute levels and of differences between the two sale dates).

Table 2 shows that, even if we use information about climate changes over shorter time-periods than those in Section 3.1, the climate trends are similar to those observed for the whole of France between 1996 and 2019. In particular, while the temperature increase is on average three to four times smaller than in Section 3.1, the average increase in temperature in spring and summer (0.31 and 0.25 respectively) is still two to three times greater than the increase in temperature in autumn and winter (0.17 and 0.10 respectively). Precipitation also changes in a similar way in our repeat-sales sample as in the remainder of France, with average increases in all seasons except spring. More importantly, temperatures and precipitation are still largely heterogeneous across the repeat-sales sample. For example, the coefficients of variation in temperature change remain greater than one. The coefficients of variation in precipitation change are even larger in our repeat-sales sample than those in Section 3.1. We thus hope that this heterogeneity of climate changes across observations, even for plots that were quickly resold, is sufficient to estimate our repeat-Ricardian models. We present the results of these estimations in the following Section.

4 Results

Section 4.1 presents the results of the estimations of the Ricardian and repeat-Ricardian models using pooled and plot fixed effects respectively. We perform sensitivity analyses on (i) the functional form, (ii) the length-definition of climate and (iii) the length of time between two sale dates in

[12]Data available at: https://esdac.jrc.ec.europa.eu/content/european-soil-database-v20-vector-and-attribute-data.
[13]Data available at: https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-30-arc-qt-science_center_objects=0#qt-science_center_objects.
[14]We only introduce altitude into the Ricardian models because of the high correlation between slope and altitude.

Table 2: Summary statistics for the plots in the repeat-sale samples, expressed in levels and differences between the two sale dates (N=8,614)

Levels	Mean	S.D.	Min	Q1	Median	Q3	Max
Farmland price (€/ha)	9,132.69	16,505.61	0.54	2,549.81	4,214.23	8,251.14	273,583.22
log(farmland price) (€/ha)	8.48	1.04	-0.62	7.84	8.34	9.02	12.52
Year of transaction	2008	6.73	1996	2003	2008	2014	2019
Farmland area (ha)	2.99	4.79	0.01	0.50	1.29	3.27	105.17
Spring temperature (°C/day)	10.05	1.62	-0.78	9.20	9.83	10.87	14.48
Summer temperature (°C/day)	18.03	2.27	0.07	16.69	17.89	19.24	23.57
Autumn temperature (°C/day)	11.44	1.69	0.04	10.52	11.26	12.34	16.40
Winter temperature (°C/day)	4.50	1.67	-4.96	3.43	4.46	5.78	9.02
Spring precipitation (cm/month)	6.64	1.46	0.04	5.74	6.40	7.16	14.40
Summer precipitation (cm/month)	5.86	1.70	0.04	4.96	5.83	6.63	16.40
Autumn precipitation (cm/month)	8.13	1.82	0.04	6.84	7.86	9.21	22.77
Winter precipitation (cm/month)	7.13	1.92	0.03	5.83	6.88	8.22	17.51
Municipal population density (inhabitants/km^2)	103.53	210.11	0.83	25.63	48.79	102.48	4767.22
Altitude (m)	190.76	212.50	1.00	69.27	135.42	225.52	2,217.23
Slope (%)	2.61	3.68	0.00	0.88	2.61	2.79	39.23
Soil (category 1)	0.12	0.25	0.00	0.00	0.00	0.05	1.00
Soil (category 2)	0.43	0.40	0.00	0.00	0.33	0.86	1.00
Soil (category 3)	0.35	0.40	0.00	0.00	0.10	0.75	1.00
Soil (category 4)	0.10	0.25	0.00	0.00	0.00	0.00	1.00
Differences between t_2 and t_1							
Farmland price (€/ha)	2,621.18	9,936.48	-103,389.66	-82.37	721.55	2,598.78	154,876.42
log(farmland price) (€/ha)	0.27	0.62	-9.18	-0.02	0.18	0.51	4.10
Spring temperature (°C/day)	0.31	0.27	-0.06	0.08	0.23	0.46	1.47
Summer temperature (°C/day)	0.25	0.23	-0.13	0.07	0.18	0.36	1.41
Autumn temperature (°C/day)	0.17	0.19	-0.52	0.03	0.11	0.27	1.02
Winter temperature (°C/day)	0.10	0.18	-0.92	-0.02	0.06	0.19	1.25
Spring precipitation (cm/month)	-0.04	0.26	-1.45	-0.18	-0.03	0.11	1.11
Summer precipitation (cm/month)	0.12	0.27	-1.25	-0.04	0.08	0.25	1.33
Autumn precipitation (cm/month)	0.09	0.32	-1.08	-0.11	0.05	0.24	2.31
Winter precipitation (cm/month)	0.01	0.36	-2.56	-0.15	0.01	0.17	1.77
Municipal population density (inhabitants/km^2)	4.77	15.96	-139.51	-0.03	1.29	5.53	409.01

The "Levels" section expressed the summary statistics of the repeat sale sample for the 8,614 transactions treated independently. The "Differences between t_2 and t_1" section expressed the summary statistics for differences between the second and first sale years for the 4,307 plots that made up our repeat sale sample.

Sections 4.2, 4.3 and 4.4 respectively. Finally, we run heterogeneity analyses on the role of irrigation and initial climates in Sections 4.5 and 4.6.

4.1 Comparisons between Ricardian and Repeat-Ricardian analyses: Pooled vs. Plot Fixed Effect estimates

Table 3 shows the estimates of the log-linear Ricardian model using pooled and plot fixed effect estimators, both in their simplest version (model 1) and with more complete versions including control variables or annual dummies (models 2 to 4). Before examining our repeat-Ricardian estimates, we first analyse the pooled Ricardian estimates (left-hand columns in Table 3).

Pooled Ricardian estimates. The left-hand columns in Table 3 provide pooled estimates of the Ricardian models, from their simplest to their most complete form. Looking first at the simplest Ricardian model (model 1), we find, in line with the literature (e.g. Mendelsohn et al., 1994; Van Passel et al., 2017; Bozzola et al., 2018), that spring and autumn temperatures increase farmland values while summer and winter temperatures decrease them. Still consistent with the remainder of the literature, we find that the pooled estimates are higher for temperature than for precipitation. For example, we find that an increase of 1 °C/day in winter temperature reduces farmland values by 27% on average, while an increase of 1 cm/month in winter precipitation reduces farmland prices by 9%.[15] Actually, our estimates are very similar to those obtained in previous Ricardian analyses in Europe. For example, all our estimates for temperatures are statistically equivalent at the 5% level to those of Van Passel et al. (2017). Our estimates for precipitation are closer to those of Vaitkeviciute et al. (2019). One sharp difference from previous Ricardian studies is that we do not find any impact of summer precipitation on farmland values.

Comparing pooled estimates from model 1 with those of models 2 to 4 highlights the fact that our estimates are sensitive to omitted farmland characteristics and annual variables. First, looking at model 2, we find that the introduction of commonly used time-(in)variant plot and municipal controls have marginal effects on the pooled estimates. Except for autumn and winter precipitation, all estimates are statistically identical between models 1 and 2. This suggests that usual controls introduced into Ricardian analyses do not correct for large omitted variable issues, at least for pooled Ricardian models.

Second, looking at model 3, we find that the amplitudes of all the estimates reduce once annual dummies are introduced (except for autumn temperatures). This is particularly the case for temperatures. For example, the impacts of an additional 1°C/day in summer drop from -19% to -9%. This suggests that 30-year averages of summer temperature are positively correlated to sale years. In particular, as temperatures tend to increase over the panel period, the addition of annual dummies removes potential trend issues. By comparison, estimates of seasonal precipitation variables are less affected by the introduction of annual dummies because precipitation changes are more heterogeneous than temperature changes across locations (Section 3.1). The introduction of annual dummies does not control for any common trend issues in precipitation changes.

Finally, the inclusion of control variables together with annual dummies in model 4 lead to estimates that quite largely differ from those in previous Ricardian models, particularly from models 1 and 2. The instability of the Ricardian estimates with regard to the inclusion of controls or annual

[15] The corresponding elasticities are -1.20±0.44 and -0.59±0.11 respectively.

Table 3: Pooled and Repeat-Ricardian estimates

	Dependent variable: log(price)							
	Pooled Ricardian				Repeat-Ricardian			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Temperature (°C/day)								
Spring	0.28 ***	0.26 ***	0.08	-0.22 ***	0.36 ***	0.36 ***	0.34 ***	0.35 ***
	(0.05)	(0.05)	(0.05)	(0.08)	(0.10)	(0.10)	(0.11)	(0.11)
Summer	-0.19 ***	-0.17 ***	-0.09 **	0.08	0.26 **	0.26 ***	0.25 **	0.25 **
	(0.04)	(0.04)	(0.05)	(0.06)	(0.11)	(0.11)	(0.12)	(0.12)
Autumn	0.26 ***	0.25 ***	0.28 ***	0.21 **	0.15 **	0.15 **	0.12	0.13
	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
Winter	-0.27 ***	-0.26 ***	-0.20***	-0.10	-0.22 ***	-0.23 ***	-0.19 ***	-0.20 ***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
Precipitations (cm/month)								
Spring	-0.18 ***	-0.18 ***	-0.17 ***	-0.11 ***	0.00	0.00	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Summer	0.01	0.01	0.01	0.00	0.10 ***	0.10 ***	0.11 **	0.10 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Autumn	0.14 ***	0.10 ***	0.11 ***	0.08 ***	0.03	0.04	0.03	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
Winter	-0.09 ***	-0.06 ***	-0.09 ***	-0.08 ***	0.07 **	0.07 **	0.06 *	0.06 *
	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
Number of observations	8,614	8,614	8,614	8,614	8,614	8,614	8,614	8,614
Time invariant plot controls		Yes		Yes				
Time invariant municipal controls		Yes		Yes				
Time variant municipal controls		Yes		Yes		Yes		Yes
Annual dummies			Yes	Yes			Yes	Yes
Plot fixed effects					Yes	Yes	Yes	Yes
Adjusted R2	0.09	0.14	0.10	0.16	0.14	0.14	0.14	0.14

*Climatologies are computed using 30-year averages. Plot controls solely include plot size. Time invariant municipal controls include average altitude and soil conditions. Time variant municipal controls solely include population density. Robust standard errors are indicated within brackets. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

dummies has already been highlighted in the literature (Deschênes and Greenstone, 2007; Ortiz-Bobea, 2020), and usually constitute a proof of the presence of an omitted variable bias in common Ricardian analysis. According to Massetti and Mendelsohn (2011), this pooled model that include both annual dummies and controls (model 4) is however likely to be the one that provide the less biased estimates. The best illustration of potential omitted variable biases in models 1 to 3 appears when looking at the estimates of seasonal temperatures in model 4. Indeed, except for autumn temperatures, all seasonal temperatures present estimates that are statistically different with those in models 1 and 2. The estimate for spring temperatures in model 4 (negative) is even statistically different to the one in model 3. The estimates for summer and winter temperatures are non-statistically different from zero. The amplitudes of the estimates for precipitation reduce, but to a lesser extent (they remain significantly different from zero, except for summer precipitation).

Repeat-Ricardian estimates. The right-hand columns in Table 3 provide plot fixed effect estimates of the repeat-Ricardian models, from their simplest to their most complete form. Any difference from pooled estimates would suggest that the introduction of the usual control variables in Ricardian analyses does not sufficiently correct for omitted variable biases. Our results show that, indeed, some plot fixed effect estimates (right-hand columns) are statistically different from the pooled estimates (left-hand columns).

First, summer temperatures *increase* farmland values in our repeat-Ricardian analysis, while summer temperatures *reduce* farmland values in the pooled Ricardian analysis. We find in the repeat-Ricardian estimation that an additional 1°C/day in summer increases farmland prices by 25% (significant at the 5% statistical level minimum), while the statistically significant estimates for the pooled estimates suggest a reduction in farmland prices by -9% to -19%. The other parameters for temperature are less influenced by the inclusion of plot fixed effects. For example, the estimates of autumn and winter temperatures are statistically equal using the two different estimators, even though the central estimates are closer to zero in the repeat-Ricardian analysis. The repeat-Ricardian estimates for spring temperature are equal to 35% (significant at the 1% statistical level) and, compared to the pooled estimates, remain stables in the four models. The repeat-Ricardian estimates for spring temperature are statistically equal to the pooled estimates in models 1 and 2. However, they are statistically different from the pooled estimates in models 3 and 4.

Second, several of the repeat-Ricardian estimates for precipitation are significantly different from the common Ricardian estimates. In particular, we find that summer precipitation positively affects farmland values, while the pooled estimates indicate no significant impact. Winter precipitation positively affects farmland values in the repeat-Ricardian analysis, while it decreases farmland values in the pooled Ricardian analysis. The repeat-Ricardian estimates also suggest that spring and autumn precipitation has no impact on farmland values once control for fixed plot characteristics. Thus, all repeat-Ricardian estimates of seasonal precipitation are different from the standard pooled Ricardian estimates. This suggest that precipitation (or water availability) is correlated with usually omitted time-invariant plot characteristics (e.g. plot's location in its watershed) and that the introduction of plot fixed effects capture most of the heterogeneity in precipitation conditions. This would imply that the impact of climate on farmland prices has been overstated in previous Ricardian studies.

Third, the repeat-Ricardian estimates are remarkably stable to the inclusion of control variables or annual dummies. None of the repeat-Ricardian estimates differs between the four models. This constitutes a sharp difference with common pooled Ricardian estimates, which were sensitive to these inclusions. The stability of our estimated parameters to the addition of control variables and annual dummies strongly support the use of plot fixed effect estimators instead of pooled estimators.

Implications. This first analysis underlines that the omitted variable bias in the Ricardian analysis may be more pronounced that initially thought. Indeed, several of the estimates for temperatures and precipitation are statistically different between our pooled Ricardian and repeat-Ricardian analyses. This is particularly true for summer temperatures, for which we find a negative impact on farmland value in standard pooled Ricardian analyses (as usually found in the Ricardian literature), but a positive impact in the repeat-Ricardian analysis. To illustrate the difference of the impacts of summer temperature between the two estimators, we project a simple additional 1°C/day in summer onto the average farmland price in our sample. While the standard pooled Ricardian analysis suggests a *reduction* in farmland price from -1,134 to -2,336€/ha (with a risk of 10%, using estimates from model 1), the repeat-Ricardian analysis suggests an *increase* of between 722 and 4,027€/ha (with a risk of 10%, using estimates from model 1). The four repeat-Ricardian estimates incate similar increase of about 2,300€/ha for each additional 1°C/day in summer. This result implies that summer temperatures may not be as detrimental to agriculture as they are usually recognized to be in the Ricardian literature. It actually suggests that farmers are likely to benefit from warmer summer temperatures in the long term. For example, farmers could switch crop allocation towards high-value crops that benefit from warm summers (Seo and Mendelsohn, 2008; Aragón et al., 2021) such as vineyards or orchards in France.

This last explanation (crop switching towards high-value crops) is consistent with the potential role of plot fixed effects in changing standard Ricardian results. Indeed, fruit productions – in particular orchards and vineyards – need particular topological and soil conditions. For example, vineyards – that benefit from warm temperatures in summer – are usually located on arid hillsides. Due to these particular characteristics, these plots may be correlated with climate conditions. Thus, once plot fixed effects are introduced in the Ricardian analysis, the resulting estimates are freed from any bias due to these particular soil and topologically characteristics. The repeat-Ricardian estimates are thus more likely to recover the unbiased impacts of climate on these plot values.

This explanation may also be consistent with the results from the panel approach that regresses crop yields or profits on weather fluctuations, despite they usually find detrimental effects of warmer summer temperatures on crop yields and profits (e.g. Schlenker and Roberts, 2009; Gammans et al., 2017). Indeed, while these studies also include individual fixed effects (however at a higher aggregated scale than the plot level), they only capture short-term adaptation. In particular, because they assume fixed crop-allocation, they are not able to account for any switch towards high-value crops.[16] To sum up, while this panel literature suggests a negative relationship between higher temperatures in summer and crop values *for each crop independently* (short-term adaptation), our results suggest a positive relationship between higher temperatures in summer and crop values *as long as crop switching is allowed* (long-term adaptation), as in the (repeat-)Ricardian analysis. The consequence is that the panel approach overestimates the costs of warmer summer temperatures.

4.2 Sensitivity analysis: functional form

Previously presented Ricardian estimates could be biased if their functional form was mis-specified. In particular, while first Ricardian studies used linear models (e.g. Mendelsohn et al., 1994), Schlenker et al. (2005) showed that log-linear models better fit farmland values. However, because log-linear models suppose that the estimated marginal value of climate is constant in level, several cross-sectional Ricardian studies have also estimated log-quadratic models (with the addition of quadratic terms for the independent variables in equations (6) and (8)). In this latter case, the marginal value of climate depends on the climate levels. The log-quadratic Ricardian model is thus particularly suited when climate varies a lot with location (Massetti and Mendelsohn, 2011). We thus re-estimate the pooled and repeat-Ricardian models using log-quadratic functional forms and compare them with those obtained preiously with the log-linear functional forms. Table 4 presents the marginal values of seasonal climatologies when using log-linear Ricardian models or log-quadratic Ricardian models with pooled or plot fixed effect estimators.

The amplitudes of the estimates depend heavily on the choice of the functional form in the pooled Ricardian analysis (Table 4). For example, the marginal impacts of autumn temperatures double in the log-quadratic model. By comparison, the estimates are much more stable in the repeat-Ricardian analysis, with only marginal differences between the different functional forms. In particular, we confirm that summer temperatures significantly increase farmland values by between 25% and 33% with the two functional forms. The marginal differences between the estimates of the two functional forms in the repeat-Ricardian analysis are probably explained by the use of heterogeneous climate changes with sale dates that are rather close to one another, which typically represent changes in temperature of some tenths of a degree Celsius or so (see Section 3.1). Log-quadratic Ricardian models thus provides little additional flexibility to our repeat-Ricardian model.

[16]Panel studies have also usually focused on the most frequently-planted crops such as cereals and other annual cash crops. Apart from Dalhaus et al. (2020), we are not aware of any panel study focusing on these high-value – often permanent – crops.

Table 4: Marginal values of seasonal climatologies for log-linear and log-quadratic Ricardian models in the Pooled and Repeat-Ricardian analyses

	Dependent variable: log(price)							
	Pooled Ricardian				Repeat-Ricardian			
	Linear		Quadratic		Linear		Quadratic	
	Model 2	**Model 4**	**Model 2**	**Model 4**	**Model 2**	**Model 4**	**Model 2**	**Model 4**
Temperature (°C/day)								
Spring	0.26 ***	-0.22 ***	0.02	-0.51 ***	0.36 ***	0.35 ***	0.29 **	0.30 **
	(0.05)	(0.08)	(0.06)	(0.08)	(0.10)	(0.11)	(0.12)	(0.12)
Summer	-0.17 ***	0.08	-0.06 *	0.17 **	0.26 ***	0.25 **	0.33 **	0.33 **
	(0.04)	(0.06)	(0.04)	(0.06)	(0.11)	(0.12)	(0.13)	(0.13)
Autumn	0.25 ***	0.21 **	0.47 ***	0.58 ***	0.15 **	0.13	0.14 *	0.14 *
	(0.07)	(0.08)	(0.07)	(0.09)	(0.07)	(0.08)	(0.08)	(0.08)
Winter	-0.26 ***	-0.10	-0.34 ***	-0.29 ***	-0.23 ***	-0.20 ***	-0.14 *	-0.14 *
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
Precipitations (cm/month)								
Spring	-0.18 ***	-0.11 ***	-0.27 ***	-0.16 ***	0.00	-0.02	0.01	0.00
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Summer	0.01	0.00	0.07 ***	0.04 *	0.10 ***	0.10 ***	0.10 **	0.10 **
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)	(0.05)
Autumn	0.10 ***	0.08 ***	0.06 ***	0.02	0.04	0.03	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Winter	-0.06 ***	-0.08 ***	0.01	-0.01	0.07 **	0.06 *	0.02	0.02
	(0.00)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Number of observations	8,614	8,614	8,614	8,614	8,614	8,614	8,614	8,614
Time invariant plot controls	Yes	Yes	Yes	Yes				
Time invariant municipal controls	Yes	Yes	Yes	Yes				
Time variant municipal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual dummies		Yes		Yes		Yes		Yes
Plot fixed effects					Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.16	0.16	0.18	0.14	0.14	0.14	0.14

*Climatologies are computed using 30-year averages. Plot controls solely include plot size. Time invariant municipal controls include average altitude and soil conditions. Time variant municipal controls solely include population density. Robust standard errors are indicated within brackets. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

4.3 Sensitivity analysis: length-definition of climate

So far, we have measured climate as 30-year averages of seasonal weather conditions, as in standard Ricardian studies (Mendelsohn and Massetti, 2017). However, our repeat-sales occurred within less than 23 years, implying that the climatologies measured on 30-year averages use weather conditions from similar years for the two sale years (at least 30-23=7 common years). Similarly to Schlenker et al. (2006), Burke and Emerick (2016) or Hsiang (2016), we thus provide robustness checks using shorter length-definitions of climate. In particular, we re-perform our repeat-Ricardian analysis using 5-, 10-, 15- and 20-year averages of seasonal weather conditions instead of 30-year averages. Table 5 compiles the plot fixed effect estimates with the alternative length-definitions of climate for model 4 (that includes annual dummies and time variant controls).

Table 5: Repeat-Ricardian estimates with alternative climate definitions

	Dependent variable: log(price)				
	30 years	**20 years**	**15 years**	**10 years**	**5 years**
Temperature (°C/day)					
Spring	0.35 ***	0.38 ***	0.19 ***	0.13 **	0.04
	(0.11)	(0.08)	(0.10)	(0.06)	(0.03)
Summer	0.25 **	0.21 **	0.34 ***	0.05	-0.05 *
	(0.12)	(0.09)	(0.06)	(0.05)	(0.03)
Autumn	0.13	0.19 ***	0.22 ***	0.38 ***	0.35 ***
	(0.08)	(0.05)	(0.04)	(0.03)	(0.03)
Winter	-0.20 ***	-0.22 ***	-0.20 ***	-0.11 ***	-0.02
	(0.07)	(0.05)	(0.04)	(0.03)	(0.02)
Precipitations (cm/month)					
Spring	-0.02	0.09 ***	0.06 **	0.02	0.00
	(0.04)	(0.03)	(0.02)	(0.01)	(0.01)
Summer	0.10 ***	0.06 ***	0.07 ***	0.01	-0.00
	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Autumn	0.03	0.06 ***	0.04 ***	0.00	-0.04 ***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Winter	0.06 *	0.03	-0.02	0.00	-0.02 **
	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
Number of observations	8,614	8,614	8,614	8,614	8,614
Time variant municipal controls	Yes	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.14	0.13	0.13	0.13

*Climatologies are computed for different periods. Time invariant municipal controls solely include population density. Robust standard errors are indicated within brackets. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

Our results in Table 5 are qualitatively similar to those in Table 3, at least for length-definitions of climate higher than 10-year averages. Indeed, all repeat-Ricardian estimates for temperatures and precipitation are statistically equal at 10% when we use the climate length-definitions of 10-, 15-, 20- and 30-year averages. All the significantly positive (resp. negative) parameters remain positive (resp. negative). In particular, we confirm that summer temperatures positively impact farmland values, but at a decreasing rate as the length-definition of climate reduces. When climate is defined as 5-year averages of seasonal weather conditions, summer temperatures decrease farmland values. Winter precipitation negatively affects farmland values, while it increased them when using longer length-definition of climate. Actually, only autumn temperatures consistently affect (increase) farmland values for all length-definition of climate (including 5-year averages). Its central estimates is however higher by about 300% compared to its estimate using 30-year averages, suggesting that autumn temperature mainly affect farmland prices due to recent increases. This result is different with the other climate variables, which rather show higher correlations with farmland prices when the length-definition of climate increases.

Overall, our results are robust to the length-definition of climate. In particular, we do find positive impacts of summer temperatures on farmland values for all length-definitions of climate (except for 5-year averages). This sensitivity analysis also suggests that farmland values present long-term relationships with temperatures as estimates are larger and, overall, more precisely estimated as the length-definition of climate increases.

4.4 Sensitivity analysis: length between two sale dates

Table 6 presents the repeat-Ricardian estimates when estimating the repeat-Ricardian model over three sub-samples for which the length between two sale dates is between (i) 1 and 5 years (representing 53.06% of the whole sample), (ii) 6 and 10 years (23.80% of the whole sample) and (iii) 11 and 23 years (23.14% of the whole sample). In line with the reduction in the number of observations, the estimates for temperature are less precise for the sub-samples. However, they are not statistically different from those for the whole sample.

Table 6: Repeat-Ricardian estimates for sub-samples differing according to the length of time between two sale dates

	Dependent variable: log(price)			
	All	**1-5 years**	**6-10 years**	**≥11 years**
Temperature (°C/day)				
Spring	0.35 ***	1.09 ***	0.48 **	-0.21
	(0.11)	(0.24)	(0.22)	(0.19)
Summer	0.25 **	0.44 *	0.15	0.37 **
	(0.12)	(0.24)	(0.24)	(0.18)
Autumn	0.13	0.05	0.06	0.01
	(0.08)	(0.16)	(0.18)	(0.13)
Winter	-0.20 ***	-0.43 ***	-0.18	0.09
	(0.07)	(0.13)	(0.16)	(0.14)
Precipitations (cm/month)				
Spring	-0.02	-0.05	-0.09	-0.04
	(0.04)	(0.07)	(0.07)	(0.06)
Summer	0.10 ***	0.12	0.28 ***	-0.01
	(0.04)	(0.09)	(0.08)	(0.08)
Autumn	0.03	-0.13 **	0.02	0.09 *
	(0.03)	(0.06)	(0.06)	(0.05)
Winter	0.06 *	0.09	-0.11 *	0.09 *
	(0.03)	(0.07)	(0.06)	(0.05)
Number of observations	8,614	4,520	2,068	2,026
Time variant municipal controls	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.09	0.17	0.24

*Climatologies are computed using 30-year averages. Time invariant municipal controls solely include population density. Robust standard errors are indicated within brackets. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

This sensitivity analysis allows us to identify which part of the repeat-sale observations drive our main results. For example, we find that the positive impact of spring temperatures on farmland values is driven by the set of plots that were re-sold in the ten first years. We find that the negative impact of winter temperatures on farmland values is rather driven by the set of farmlands that were re-sold shortly after the first sale. Although the central estimates are positive for all sub-samples, the estimated impacts of autumn temperatures are non-significantly different from zero. Finally, the estimates for summer temperature are all positive, but only significantly different from zero for the 1-5 years and 11-23 years sub-samples. Actually, other seasonal temperatures do not affect farmland prices in the 11-23 years sub-samples, implying that the only significant impact of long-term changes in temperature is driven by long-term changes in summer temperatures. This suggest that farmers' long-term adaptation to changes in temperature is beneficial.

Similarly, we find that the positive impact of summer precipitations is driven by the 6-10 years sub-samples. However, the results are overall less consistent for precipitation than temperatures across sub-samples. Indeed, the impacts of precipitation are rather heterogeneous for the different sub-samples, and not precisely estimated. For example, autumn and winter temperatures affect either positively or negatively farmland values depending on the sub-samples. The positive impacts concern the 11-23 years sub-sample, suggesting that, as for temperatures, farmers' long-term adaption to precipitation changes mainly occur to long-term changes in climate. The fact that farmland values rather share a long-term relationship with climate change is also supported by the evolution of adjusted R^2 between the different sub-samples, which increase from 0.09 for the 1-5 years sub-sample to 0.24 for the sub-sample of plots which are re-sold after 11 years.

This sensitivity analysis based on selecting observations according to the time between sale dates shows that the estimates for the different sub-samples are not statistically different. More importantly, they are not statistically different from those in the whole sample, giving us confidence in our main estimates.

4.5 Heterogeneity analysis: the role of irrigation

The Ricardian analysis proposed by Mendelsohn et al. (1994) has been criticized for overlooking the role of irrigation (Schlenker et al., 2005). Indeed, it is likely that irrigated and rainfed agriculture do not adapt to or benefit from climate change in similar ways. For example, farmers in irrigated farmlands could be better able to benefit from higher summer temperatures since they can reduce crop heat stress by providing water. Consequently, Schlenker et al. (2005) proposed that the

Ricardian analysis should be performed on two separate sub-samples: one consisting of rainfed counties and the other of irrigated counties.

Accordingly, we perform our repeat-Ricardian analysis on sub-samples consisting of irrigated or rainfed farmland. Unfortunately, our database does not indicate whether the plots that were sold are irrigated or not. We thus separate our two sub-samples based on the percentage of the plots' departmental UAA subject to irrigation. Departments are administrative regions that divide France into 101 units of about equal size.[17]. We use the last available agricultural census from 2010 to separate our sample into two sub-samples based on the irrigated percentage of the departmental UAA (Lerbourg, 2012). As in Schlenker et al. (2005), we consider that an observation is part of our irrigated sample if more than 20% of its departmental UAA is irrigated (978 plots in total). All other plots (7,636) are considered to be part of the rainfed sample. Table 7 provides the repeat-Ricardian estimates for the whole sample as well as for the two sub-samples.

Table 7: Repeat-Ricardian estimates in irrigated and rainfed departments

	Dependent variable: log(price)		
	All	**Irrigated departments**	**Rainfed departments**
Temperature (°C/day)			
Spring	0.35 ***	0.18	0.37 ***
	(0.11)	(0.36)	(0.12)
Summer	0.25 **	-0.15	0.28 **
	(0.12)	(0.43)	(0.13)
Autumn	0.13	0.72 **	0.11
	(0.08)	(0.30)	(0.08)
Winter	-0.20 ***	-0.31	-0.18 **
	(0.07)	(0.23)	(0.07)
Precipitations (cm/month)			
Spring	-0.02	0.18	-0.03
	(0.04)	(0.15)	(0.04)
Summer	0.10 ***	0.46 ***	0.04
	(0.04)	(0.17)	(0.05)
Autumn	0.03	0.00	0.04
	(0.03)	(0.10)	(0.03)
Winter	0.06 *	-0.48 ***	0.09 ***
	(0.03)	(0.13)	(0.03)
Number of observations	8,614	978	7,636
Time variant municipal controls	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes
Adjusted R2	0.14	0.08	0.15

*Estimates are computed using log-linear Ricardian models. Plots are classified into two sub-samples according to whether they are in a department for which more than 15% of the UAA is irrigated. Climatologies are computed using 30-year averages. Robust standard errors are indicated within brackets. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

[17] After exclusion of Corsica, Ile-de-France and overseas territories, our sample contains 89 departments

We find that, despite noticeably different central estimates for the seasonal temperatures, the differences between the estimates of the two sub-samples are not significant. In fact, the highest difference relates to the impact of summer temperatures, which is positive in the rainfed departments, but null in the irrigated departments. The main difference relates to the impact of summer precipitation, which is positive in the two sub-samples but only significantly different from zero in the irrigated sub-sample. Consistently with Schlenker et al. (2005), we find that plots in the irrigated sub-sample benefit from larger beneficial impacts of summer precipitation compared to plots in the rainfed sub-sample. The central estimates suggest that the irrigated sub-sample benefits eleven times more from precipitation in summer (and five times more than in the whole sample), underlying the scarcity of water (and thus its value) in irrigated areas.

This heterogeneity analysis suggests that, while the beneficial impacts of summer precipitation are driven by the irrigated sub-sample, the other results (in particular the positive impacts of summer temperatures) are driven by the rainfed sub-sample.

4.6 Heterogeneity analysis: the role of initial climates

The previous regressions implicitly assumed that the climate is the same for the whole of France. However, France has four different, contrasting climates (i.e. Continental, Mediterranean, Mountain and Oceanic; see Section 3.1). Accounting for these different climates is even more relevant since agriculture in these different zones has specialized to benefit from their climate characteristics. For example, livestock farming activities (and pastures) are heavily located in regions with oceanic or mountain climates. Temporary crops (cereals and cash crops) are mainly located in continental and oceanic climates. Fruit productions are mainly located in Mediterranean regions. These agricultural regions – that thus differ in both climate and agricultural specializations – are likely to react differently to similar climate variations. We thus subdivide our initial sample into four sub-samples (one for each climate) using the geographical definition of French climate zones (Figure A2 in the Appendices) and re-perform our repeat-Ricardian analyses on these different sub-samples. Table 8 summarizes the estimates.

First, the results indicate that, overall, farmland prices in the oceanic sub-sample behave similarly to the whole sample. Indeed, while the central estimates sometimes diverge, all the parameters are statistically equal to the whole sample. In particular, the oceanic sub-sample seems to drive some of the results in the whole sample, such as the negative impact of winter temperatures, the beneficial impacts of winter precipitation or, to a lesser extent, the beneficial impacts of spring temperatures. This is probably explained by the fact that the transactions in this sub-sample

Table 8: Repeat-Ricardian estimates in different climatic regions

	Dependent variable: log(price)				
	All	**Continental**	**Oceanic**	**Mediterranean**	**Mountain**
Temperature (°C/day)					
Spring	0.35 ***	0.62 ***	0.90 ***	-0.47	0.00
	(0.11)	(0.21)	(0.20)	(0.41)	(0.36)
Summer	0.25 **	-0.25	-0.17	1.49 ***	0.39
	(0.12)	(0.22)	(0.21)	(0.45)	(0.42)
Autumn	0.13	0.06	-0.05	-0.27	0.42 **
	(0.08)	(0.14)	(0.13)	(0.33)	(0.21)
Winter	-0.20 ***	0.04	-0.42 ***	-0.18	-0.01
	(0.07)	(0.12)	(0.13)	(0.21)	(0.23)
Precipitations (cm/month)					
Spring	-0.02	0.18 **	-0.15 **	0.24 *	0.33 ***
	(0.04)	(0.07)	(0.06)	(0.13)	(0.12)
Summer	0.10 ***	0.13	0.05	0.12	-0.19
	(0.04)	(0.09)	(0.07)	(0.19)	(0.13)
Autumn	0.03	-0.07	-0.02	-0.02	-0.16
	(0.03)	(0.07)	(0.05)	(0.09)	(0.11)
Winter	0.06 *	-0.04	0.25 ***	-0.12	-0.03
	(0.03)	(0.06)	(0.05)	(0.08)	(0.16)
Number of observations	8,614	2,904	3,604	1,098	1,008
Time variant municipal controls	Yes	Yes	Yes	Yes	Yes
Annual dummies	Yes	Yes	Yes	Yes	Yes
Plot fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.14	0.14	0.20	0.13	0.08

*Estimates are computed using log-linear Ricardian model. Plots are classified into four sub-samples according to their initial climate. Climatologies are computed using 30-year averages. Time invariant municipal controls solely include population density. Robust standard errors are indicated within brackets. *, ** and *** indicate a p-value lower than 0.1, 0.05 and 0.01 respectively.*

comprised 42% of the whole sample. One noticeable difference with the whole sample (though not statistically significant) is that summer temperatures do not increase farmland values, but rather tend to be negatively correlated to them.

Second, the continental sub-sample, representing 34% of the whole sample, presents about similar results than the oceanic sub-sample. In particular, we find similarly a (statistically significant) positive impact of spring temperatures associated with a (non-significant) negative impact of summer temperatures. These results do not appear in the Mediterranean and mountain sub-samples, suggesting that the continental and oceanic sub-samples share a particularity that the two other sub-samples have not. Given the distribution of the agricultural activities across France describe above, we assume that these results reflect the impact of climate conditions on the profitability of areas that grow temporary crops. Indeed, these results are actually coherent to the literature using panel econometrics to regress temporary crop yields on weather conditions (Schlenker and Roberts, 2009; Gammans et al., 2017), who find beneficial impacts of growing-season cumulative temperatures up to 29°C (referred to as beneficial degree-days) but negative impacts afterwards (referred to as heating degree-days). Because these high temperatures are usually find in summer in France, our estimates may reflect these impacts of beneficial and heating degree-days.

Third, Table 8 indicates that, as in the whole sample, summer temperatures increase farmland values in the Mediterranean sub-sample, but by about six times more than in the whole sample. This probably reflects the specialization of Mediterranean agriculture towards vineyards and other fruits that benefit from warm summers (De Salvo et al., 2013).

Finally, the repeat-Ricardian analysis yields results in the Mountain climate that are not precisely estimated. Actually, the single precisely estimated coefficient for seasonal temperatures concerns autumn temperatures, a result that does not appear in any other sub-samples. We assume that this result reflects the positive impacts of autumn temperatures on pasture growth, that allows mountain farms (which are highly specialized towards livestock farming activities) to a longer grazing period in uplands. This feature probably explains that the estimate for autumn temperatures in the whole sample is driven by the mountain sub-sample.

Overall, this heterogeneity analysis of the role of initial climate gives us confidence in our previous results. In particular, these latter results are coherent with the panel literature on crop yields and weather, that identified negative impacts of summer temperatures for temporary crops and support our previous assumption of a negative relationship between high temperatures in summer and crop values *for each crop independently* (short-term adaptation), but a positive relationship between higher temperatures in summer and crop values *as long as crop switching – towards high-value production such as fruits – is allowed* (long-term adaptation). This last heterogeneity analysis indeed supports that high summer temperatures are beneficial to agriculture in the Mediterranean area, where most fruits and vineyards are located.

5 Simulating Climate Change Impacts

In this section we compare the estimates of the impacts of possible future climate change scenarios using the Ricardian estimates from pooled and plot fixed effect estimators. We use the spatially-explicit projections from the ALADIN climate model from Météo-France to project tailored future climate conditions for each observation of our repeat-sales sample.[18] We study the impacts of medium (2046-2069) and long (2070-2099) run outcomes under low (RCP 2.6), medium (RCP 4.5) and high (RCP 8.5) emission pathways on each plot price of our repeat-sale sample, assuming all other factors to be constant. We compute these impacts by multiplying, for

[18]Data available at: https://www.umr-cnrm.fr/spip.php?article125&lang=en

each observation, the pooled Ricardian and repeat-Ricardian estimates by the differences between future climatologies and those of the 1996-2019 period. In particular, we use the pooled and repeat-Ricardian that include control variables together (or not) with annual dummies, i.e. for Ricardian and repeat-Ricardian models 2 and 4 in Table 3. Despite our repeat-sale sample being representative of the general population, the aim of the analysis is not to forecast future climate outcomes but rather to examine the sensitivity of climate change impacts to the choice of estimators.

Figure 4 shows the aggregate percentage change in farmland values for alternative climate scenarios with 95% confidence intervals. The point estimates of climate impacts vary depending on the Ricardian models, climate change scenarios and time horizons. As is commonly the case, we find that the impacts are generally greater for longer time horizons and for larger cumulative future emission scenarios, for both pooled and repeat-Ricardian models.

Figure 4 and Table 9 underline that the pooled Ricardian estimates suggest slightly positive impacts on farmland values. All the impacts by the end of the century using pooled estimates are statistically null at a risk level of 5%. The single statistically significant positive impact of a climate scenario using our pooled estimates appears for the RCP8.5 scenario in 2046-2069 period (coupled to estimates of model 4), where we find that farmland values are likely to increase on average by between 8% and 56%. Recent European assessments of the impacts of future climate change using cross-sectional or pooled Ricardian estimates found rather similar slightly positive impacts (Bozzola et al., 2018; Fabri et al., 2021; Fezzi and Bateman, 2015; Vaitkeviciute et al., 2019). In particular, Vaitkeviciute et al. (2019) found that a similar RCP8.5 scenario could lead to an average increase of French farmland values by 38% (our estimates are statistically equivalent).

Figure 4 and Table 9 indicate that the predicted impacts using repeat-Ricardian estimates are positive and much greater than those using pooled Ricardian estimates. While eleven out of twelve of our estimated impacts using the pooled estimates are non-significantly different from zero, all the repeat-Ricardian estimates are significantly positive, though rather imprecise. For example, we find that farmland values are likely to increase on average by between 110% and 276% by the end of the century under a RCP8.5 scenario using the repeat-Ricardian model 4. Though rather imprecise, the estimated impacts using the repeat-Ricardian estimates are statistically different from those using the pooled Ricardian estimates under the RCP4.5 and RCP8.5 scenarios for the 2070-2099 period. Using the central repeat-Ricardian estimates, our simulations suggest that climate change could increase French farmland values by between 54% and 203% by the end of the century (depending on the IPCC scenario used), i.e. an increase that is more than two to twenty times greater than in

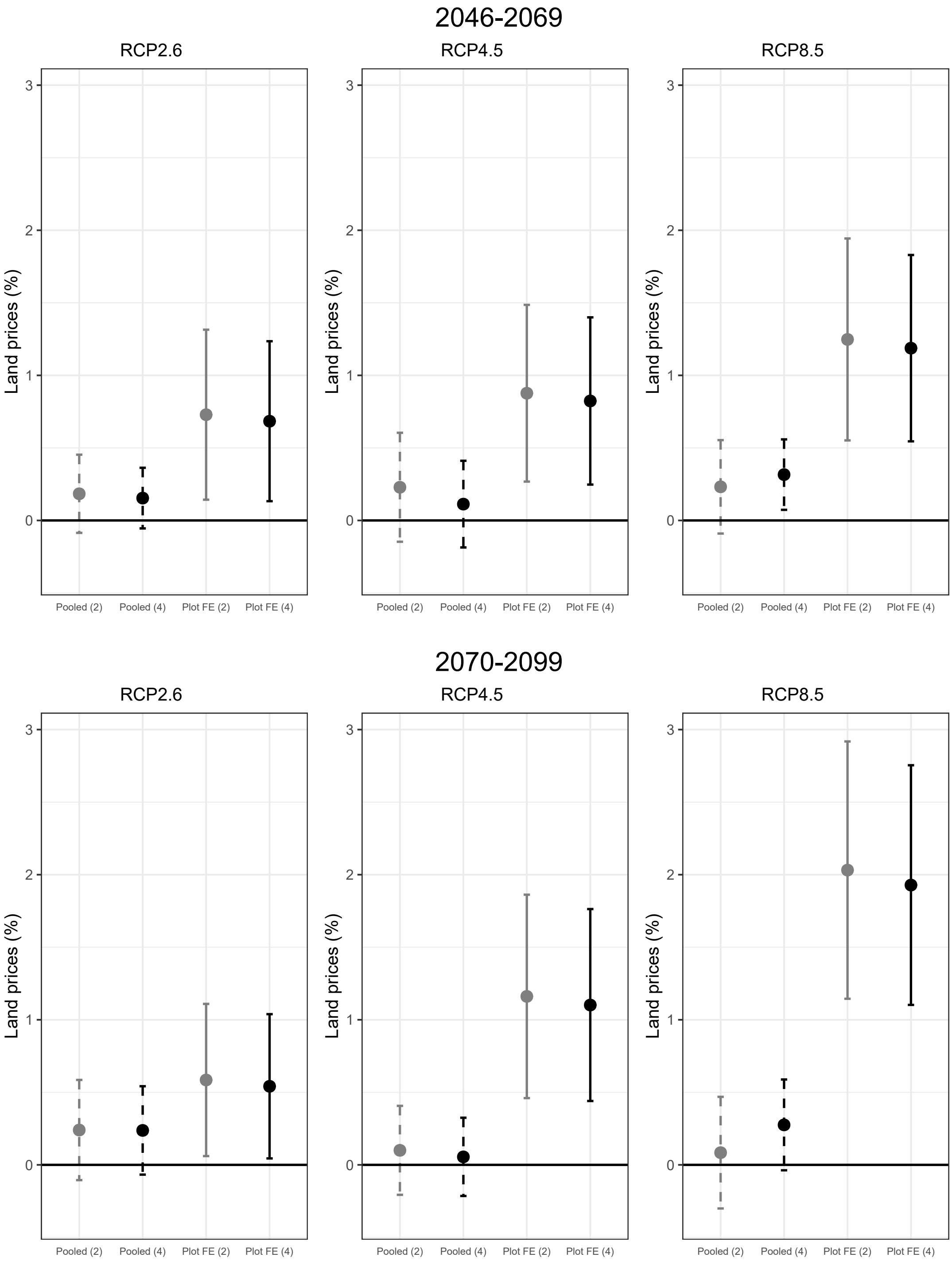


Figure 4: Climate change impacts on farmland prices for various scenarios and time horizons. *Graphs display predicted changes in farmland values by the middle and end of the century relative to the period 1996-2019. Dots represent point estimates and whiskers show the 95% confidence interval. The dashed lines correspond to pooled Ricardian models. The solid lines indicate repeat-Ricardian models. All estimates come from Ricardian models with control variables (including time invariant municipal and plot controls for the pooled models). The grey lines correspond to Ricardian models without annual dummies. The black lines indicate Ricardian models with annual dummies.*

the corresponding pooled Ricardian model (Table 9). This illustrates large omitted variable biases in common Ricardian analyses.

Table 9: Climate change impacts on farmland prices under various scenarios and time horizons using pooled Ricardian and Repeat-Ricardian estimates.

2046-2069	**Mean**	**S.D.**	**Min**	**Q1**	**Median**	**Q3**	**Max**	1 - $\frac{\hat{\text{Impacts}}_{\text{Pooled}}}{\hat{\text{Impacts}}_{\text{Repeat}}}$
RCP2.6								
Pooled Ricardian (2)	0.18	0.14	-0.85	0.10	0.20	0.27	0.72	-
Pooled Ricardian (4)	0.15	0.11	-0.57	0.10	0.15	0.22	0.50	-
Repeat-Ricardian (2)	0.73	0.29	-0.09	0.51	0.73	0.94	2.21	0.75
Repeat-Ricardian (4)	0.68	0.28	-0.09	0.47	0.68	0.88	2.01	0.78
RCP4.5								
Pooled Ricardian (2)	0.23	0.19	-0.96	0.14	0.27	0.36	0.77	-
Pooled Ricardian (4)	0.11	0.15	-0.79	0.07	0.14	0.20	0.51	-
Repeat-Ricardian (2)	0.88	0.31	0.01	0.65	0.87	1.09	2.61	0.74
Repeat-Ricardian (4)	0.82	0.29	0.01	0.61	0.82	1.02	2.38	0.87
RCP8.5								
Pooled Ricardian (2)	0.23	0.16	-1.40	0.15	0.25	0.33	0.76	-
Pooled Ricardian (4)	0.32	0.12	-0.81	0.26	0.33	0.39	0.73	-
Repeat-Ricardian (2)	1.25	0.35	0.01	1.01	1.25	1.50	2.94	0.82
Repeat-Ricardian (4)	1.19	0.32	0.01	0.97	1.19	1.42	2.69	0.73
2070-2099								
RCP2.6								
Pooled Ricardian (2)	0.24	0.17	-1.00	0.17	0.27	0.35	0.85	-
Pooled Ricardian (4)	0.24	0.15	-0.85	0.19	0.27	0.33	0.70	-
Repeat-Ricardian (2)	0.58	0.26	-0.13	0.39	0.58	0.78	1.99	0.59
Repeat-Ricardian (4)	0.54	0.25	-0.14	0.36	0.54	0.73	1.80	0.56
RCP4.5								
Pooled Ricardian (2)	0.10	0.15	-1.18	0.02	0.10	0.19	0.81	-
Pooled Ricardian (4)	0.06	0.14	-0.90	-0.01	0.06	0.13	0.51	-
Repeat-Ricardian (2)	1.16	0.35	0.01	0.92	1.16	1.41	2.90	0.92
Repeat-Ricardian (4)	1.10	0.33	0.01	0.87	1.10	1.34	2.63	0.95
RCP8.5								
Pooled Ricardian (2)	0.08	0.19	-1.89	-0.01	0.09	0.19	0.96	-
Pooled Ricardian (4)	0.28	0.16	-1.33	0.22	0.30	0.36	0.82	-
Repeat-Ricardian (2)	2.03	0.45	0.01	1.78	2.06	2.33	3.99	0.96
Repeat-Ricardian (4)	1.93	0.42	0.01	1.69	1.96	2.21	3.62	0.85

The summary statistics indicate predicted changes in farmland values by the middle and end of the century relative to 1996-2019. All estimates come from Ricardian models with control variables. Models (2) indicate Ricardian models without annual dummies. Models (4) include annual dummies. For each scenario and time horizon, the bias is calculated as the ratio between the central pooled Ricardian estimate and the central Repeat-Ricardian estimate.

The comparison of the estimated impacts between the two estimates in Table 9 underlines the fact that standard Ricardian analyses underestimate climate impacts on farmland values in our sample by between 73% and 87% for the 2046-2089 period (resp. for Ricardian models 4 under RCP 8.5 and RCP 4.5 scenario) and by between 56% to 96% for the 2070-2099 period (resp. for

Ricardian models 2 under RCP2.6 and RCP8.5 scenario). This illustrates the large omitted variable bias in standard pooled Ricardian analyses. The bias is economically important. Assuming that the French UAA remains equal to the 1996-2019 level (i.e. 27 million hectares), the pooled Ricardian estimates lead to an underestimation of 72 to 374 billion euros of the benefits of climate change for the whole of French agriculture under RCP2.6 and RCP8.5 scenarios for the 2070-2099 period.

6 Concluding Remarks

Ricardian analyses exploit cross-sectional differences in farmland prices and climate across locations to infer the costs of climate change borne by agriculture (Mendelsohn et al., 1994). While Ricardian analyses have become a cornerstone of the literature, the lack of a formal econometric strategy to deal with potential omitted variable bias sheds doubts on its ability to provide unbiased estimates. For this reason, the literature has turned towards panel analyses of weather impacts on yields and profits conditionally on individual fixed effects (Deschênes and Greenstone, 2007). However, panel analyses only account for farmers' short-term adaptation, which theoretically leads to an overestimation of the costs of climate change. At the crossroads between these two approaches, this paper proposes a new methodology, the repeat-Ricardian analysis, that corrects for omitted variable bias (as in the panel analyses) while exploiting differences in both climate and farmland prices to account for farmers' long term adaptation (as in standard Ricardian analyses). Formally, the repeat-Ricardian analysis uses repeat-sales farmland data to add plot fixed effects into standard Ricardian models. Doing so, we are able to provide an estimation of the omitted variable bias due to time-invariant plot characteristics (e.g. soil and topological characteristics) that occurs in standard pooled Ricardian analyses.

We estimate repeat-Ricardian models on the French sample of farmlands that were sold twice between 1996 and 2019 using plot fixed effects and compare the obtained estimates with those from standard pooled Ricardian models (e.g. Massetti and Mendelsohn, 2011). This sample has the triple advantage of to be available at the plot level (instead of usual aggregated data used in the Ricardian literature; Fezzi and Bateman, 2015), to provide information on *observed* land price transactions (instead of declarative land values; Bigelow et al., 2020) and to be representative of the other transactions occurring at national scale.

Our results indicate significant differences between our repeat-Ricardian estimates and the pooled Ricardian estimates. For example, while our pooled Ricardian estimates tend to confirm the negative impacts of summer temperatures on farmland values identified in previous Ricardian studies, our repeat-Ricardian estimates indicate unambiguous positive impacts of summer temperatures. We estimate that each additional 1°C in summer increases farmland values by about 25% (corresponding to about 2,300€/ha). Moreover, our repeat-Ricardian estimates are robust to the choice of the functional forms and control variables. This represents a sharp difference from the pooled estimates, whom levels can be different according to the choice of the functional forms and to the inclusion of control variables and annual dummies. As already highlighted by Schlenker et al. (2005) and Deschênes and Greenstone (2007), the instability of standard Ricardian estimates suggests large omitted variable biases in cross-section and pooled Ricardian analyses, that commonly-used control variables fail to overcome. In particular, our simulations suggest that the omitted variable biases in standard Ricardian analyses lead to an underestimation of the impacts of future climate changes on farmland values by between 56% and 96%.

The main objective of the paper was to identify and highlight the magnitude of the omitted variable biases in standard Ricardian analyses. While we propose a correction to such biases, the usual caveats of Ricardian analyses also apply to our repeat-Ricardian analyses. For example, other drivers such as commodity prices are assumed to remain constant between the scenarios (Cline, 1996). Also, we do not account for farmers' anticipation of future climate conditions (Severen et al., 2018). However, the introduction of climate forecasts in a similar fashion to that in Severen et al. (2018) could have an impact on our repeat-Ricardian estimates. Indeed, one can assume that the anticipated climate conditions by the end of the century were similar at the dates of the first and second sales in the repeat-sales sample, to the extent that they would be captured by the plot fixed effects in the repeat-Ricardian analysis. While the aim of our paper is not to produce forecasts of climate change impacts on farmland values, future applications of the repeat-Ricardian analysis could investigate how the consideration of the above-mentioned caveats modifies the measurement of climate change impacts.

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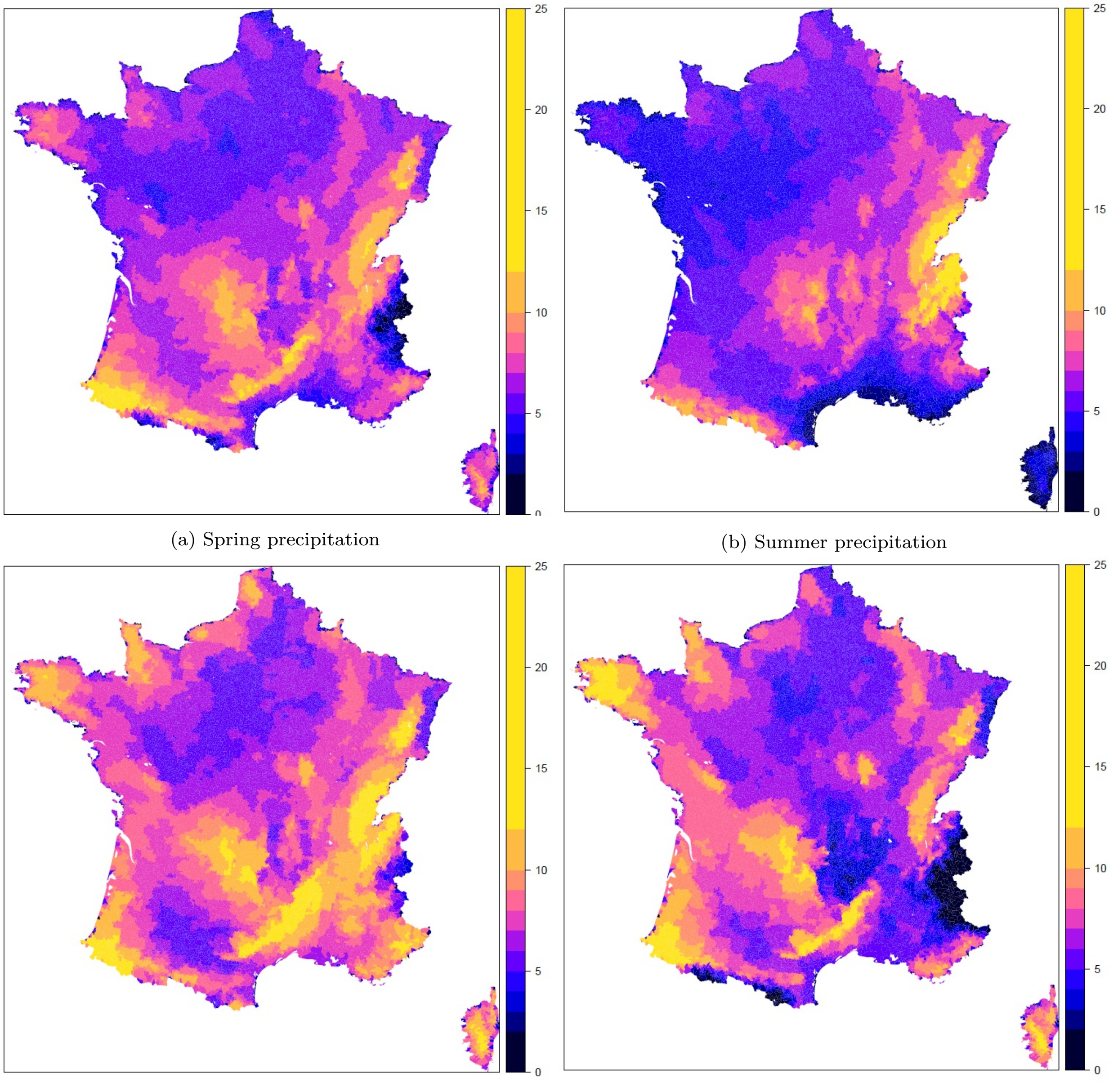
7 Appendices



(a) Spring precipitation

(b) Summer precipitation

(c) Autumn precipitation

(d) Winter precipitation

Figure A1: Seasonal precipitation for the 1966-1995 period in France. *The information is expressed in cm/day and available for the 36,486 French municipalities. Spring precipitation is computed as the average of monthly precipitation in March-May (respectively June-August, September-November and December-February for summer, autumn and winter).*

Table A1: Climate change across French municipalities between 1996 and 2019 (N=36,486)

	Mean	**S.D.**	**Min**	**Max**
Temperature (°C/day)				
Spring 1996	9.18	1.62	-3.40	13.6
Spring 2019	10.24	1.67	-2.50	14.40
Spring change 1996-2019	1.06	0.23	0.00	2.16
Summer 1996	17.39	2.00	0.01	22.70
Summer 2019	18.34	2.11	0.01	23.80
Summer change 1996-2019	0.95	0.26	0.00	2.40
Autumn 1996	10.73	1.70	0.01	16.50
Autumn 2019	11.16	1.74	0.01	17.10
Autumn change 1996-2019	0.43	0.30	-0.96	1.41
Winter 1996	3.67	1.82	-6.8	9.39
Winter 2019	4.09	1.76	-6.6	9.78
Winter change 1996-2019	0.42	0.30	-1.10	1.58
Precipitation (cm/month)				
Spring 1996	6.95	1.69	0.01	16.8
Spring 2019	6.82	1.71	0.01	15.50
Spring change 1996-2019	-0.13	0.32	-1.70	1.27
Summer 1996	6.32	1.78	0.01	15.90
Summer 2019	6.53	1.77	0.01	16.30
Summer change 1996-2019	0.21	0.38	-1.60	1.73
Autumn 1996	7.87	2.10	0.01	24.10
Autumn 2019	8.17	2.36	0.01	29.80
Autumn change 1996-2019	0.31	0.57	-1.00	5.74
Winter 1996	7.01	2.03	0.01	17.90
Winter 2019	7.04	1.97	0.01	19.50
Winter change 1996-2019	0.03	0.66	-3.10	2.11

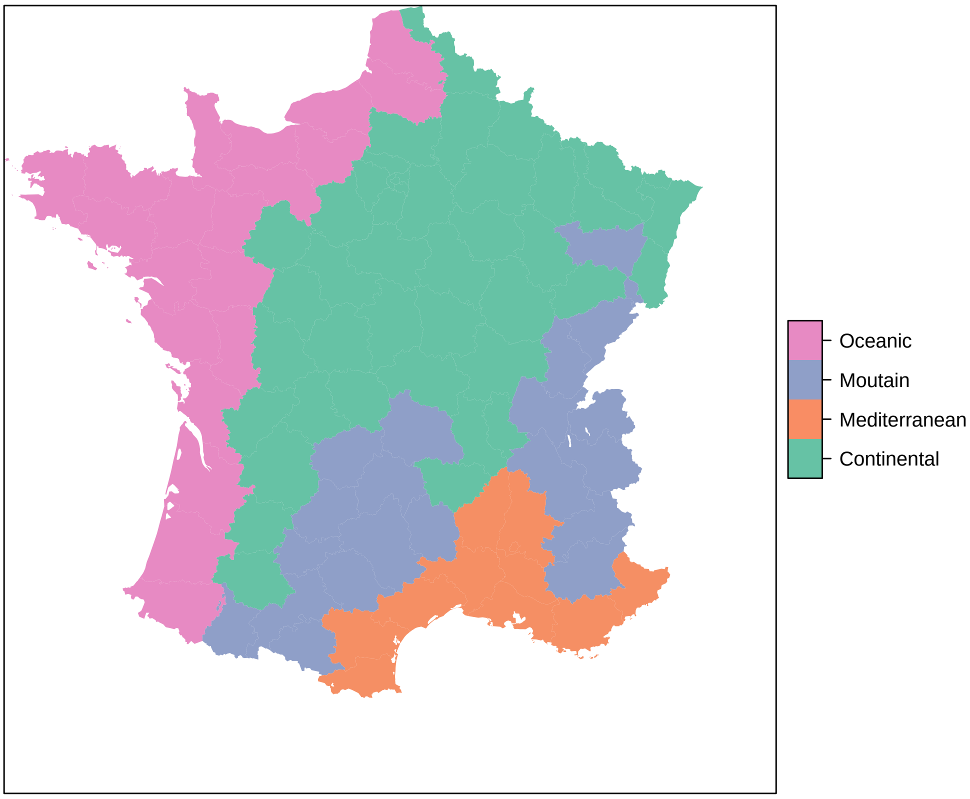
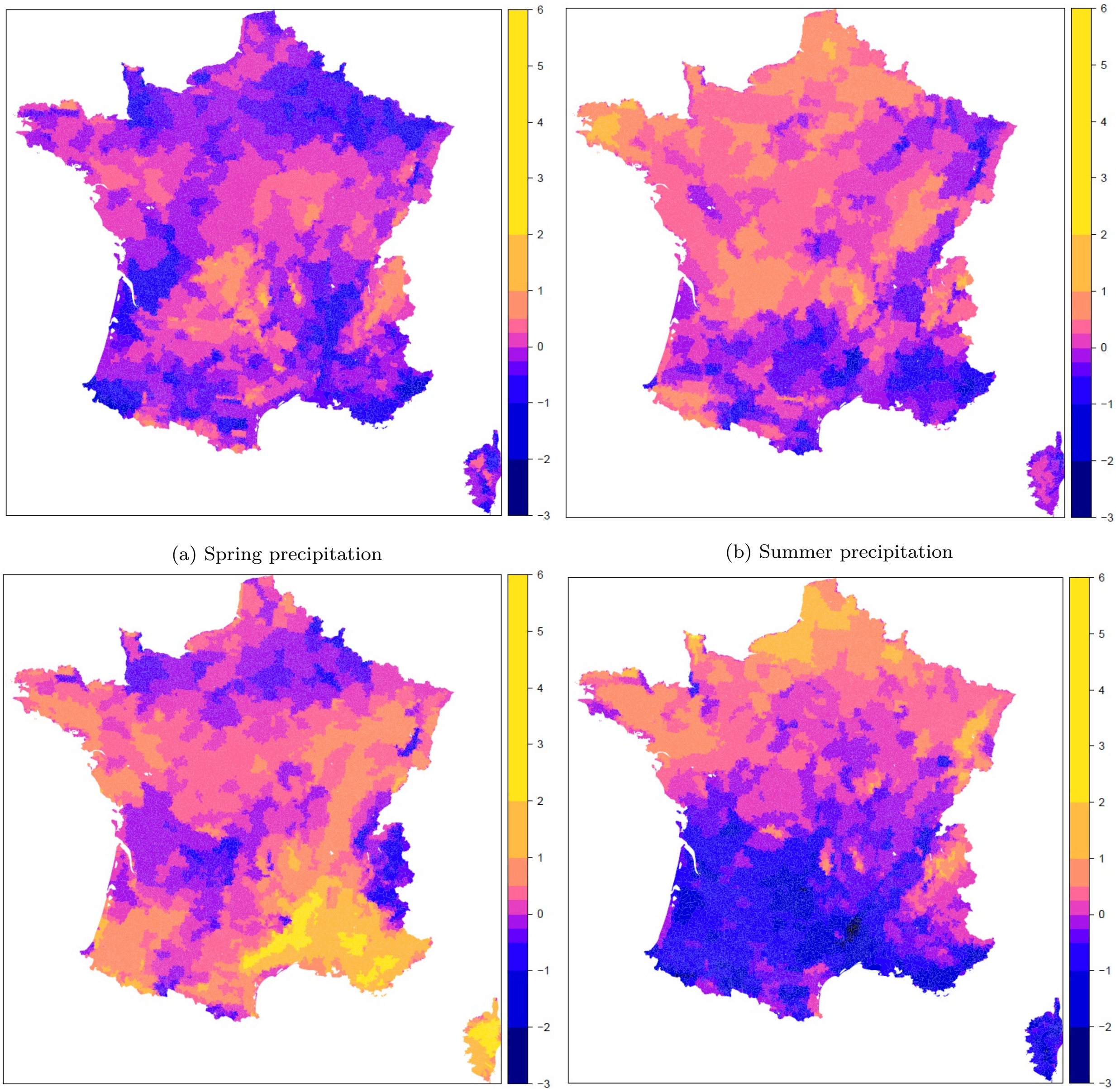


Figure A2: The diversity of French climates (Source: authors' own distribution based on Joly et al., 2010). *The continental climate is characterized by cold winters and hot summers. The oceanic climate has cool, rainy winters and summers. The Mediterranean climate has hot, dry summers. The mountain climate has snowy winters and cool summers.*



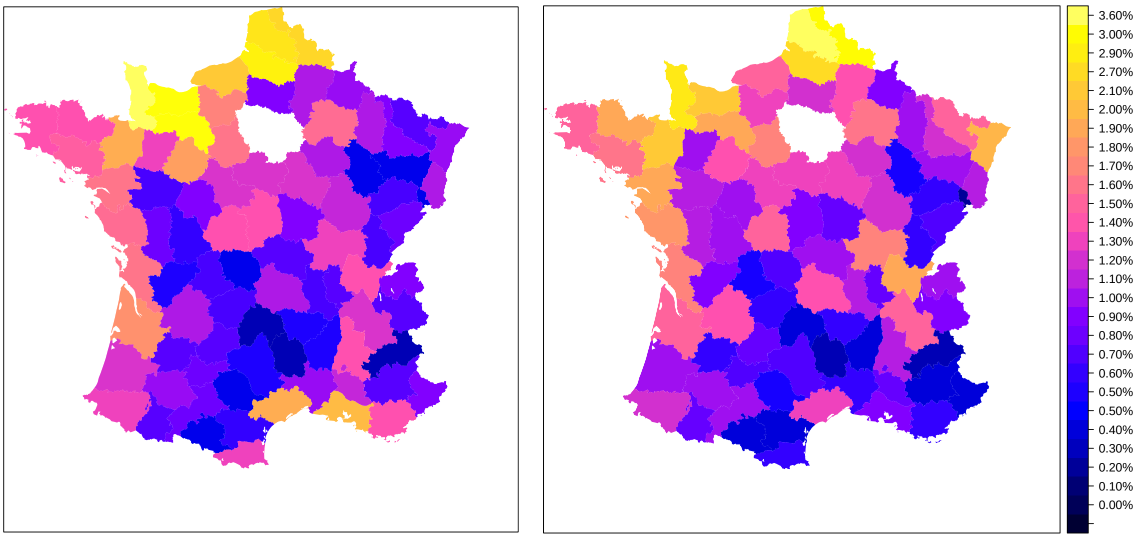
(a) Spring precipitation

(b) Summer precipitation

(c) Autumn precipitation

(d) Winter precipitation

Figure A3: Changes in seasonal precipitation from 1996 (1966-1995 averages) to 2019 (1989-2018 averages) in France. *The information is expressed in cm/month and available for the 36,486 French municipalities. Spring temperatures are computed as the 30-year averages of daily temperatures in March-May (respectively June-August, September-November and December-February for summer, autumn and winter).*



(a) Repeat sales

(b) All transactions

Figure A4: Spatial distribution of the observed transactions in (a) the repeat sales sample (N=8,814) and (b) the general population (N=660,775). *The PERVAL database provides information about transactions that occurred between 1996 and 2019 in France, excluding the Ile-de-France region. We removed Corsica because of concerns about outliers. The Figure informs on the share of the two samples that are located within each French departments.*

Table A2: Number of first- and second-sale transactions per year

	1997	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**Total**
1996	35	7	15	6	10	12	13	11	16	9	9	9	12	8	5	8	5	9	5	8	10	7	11	240
1997		35	14	10	14	7	18	13	10	9	14	8	8	9	9	11	13	9	8	8	12	12	12	263
1998			35	10	8	15	14	9	12	17	12	6	8	9	8	6	13	9	12	7	10	9	15	244
1999				27	20	16	21	18	20	16	18	17	6	9	14	12	12	5	9	9	14	12	15	290
2000					32	11	16	8	16	7	17	11	11	10	14	7	16	9	11	10	8	15	13	242
2001						37	11	11	15	17	8	13	8	10	8	11	8	12	6	14	14	11	11	225
2002							46	15	19	8	12	9	7	9	5	4	11	15	7	9	7	11	6	200
2003								53	20	12	17	22	17	8	16	20	11	11	12	8	14	14	17	272
2004									56	24	20	15	16	19	8	13	7	16	12	18	18	9	17	268
2005										46	21	20	12	18	12	15	17	15	10	10	15	24	14	249
2006											55	17	17	15	20	15	15	14	9	15	13	13	9	227
2007												40	19	20	15	9	13	15	11	9	16	25	21	213
2008													51	20	17	22	15	15	16	17	14	14	21	222
2009														47	27	17	14	19	14	12	14	21	20	205
2010															41	14	27	9	14	8	11	12	8	144
2011																32	13	18	11	10	20	20	11	135
2012																	32	18	18	13	15	14	16	126
2013																		32	22	10	15	15	26	120
2014																			30	21	26	24	18	119
2015																				45	11	13	18	87
2016																					31	22	16	69
2017																						64	21	85
2018																							62	62
Total	35	42	64	53	84	98	139	138	184	165	203	187	192	211	219	216	242	250	237	261	308	381	398	4307

The years of first sale are indicated in the left-hand column. The years of second sales are indicated along the top.

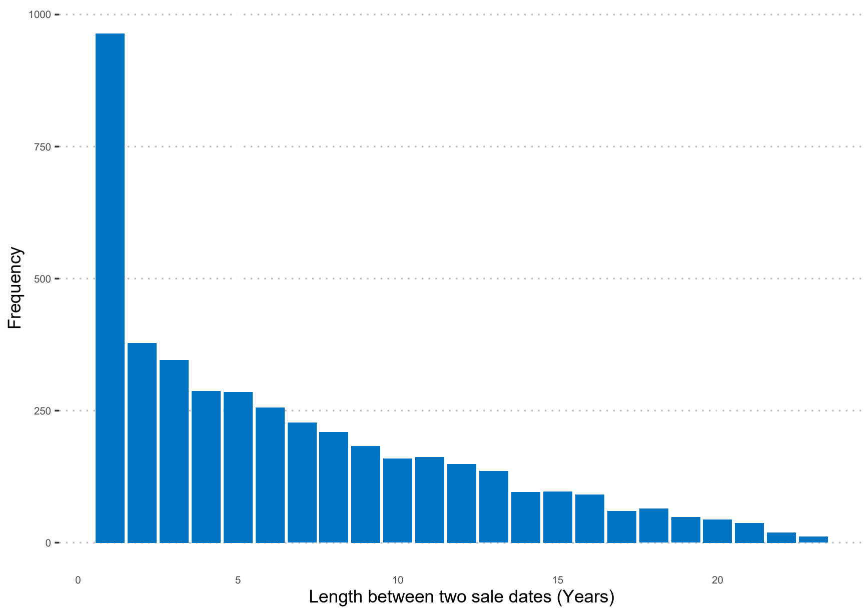


Figure A5: Frequency of the length of time between two sale dates (in years)