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CLIMATE CHANGE EFFECTS AND ECONOMIC IMPACT ON AGRICULTURAL PRODUCTION IN SICILY

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Abstract. The nature of climate change and its possible economic consequences are complex issues. This complexity results from the interaction of a large number of elements from natural and economic science. The economic impact of climate change has been extensively investigated in the contemporary literature, particularly using so-called Integrated Assessment Models. However, the sensitivity of this class of models to the chosen impulse function has switched research focus to empirical investigation of the influence of climate change on socioeconomic factors. On the other hand, while the majority of the literature focuses on economic outcomes such as productivity, the effects of climate change on financial markets, particularly on a regional scale, remain understudied. The purpose of the present work is to examine the impact of temperature and rainfall on agricultural productivity through an empirical analysis of market price time series for lemons in Sicily. On this purpose, a dataset consisting of 254 monthly observations relative to the Messina's market from January 2002 to February 2023 and a price series provided by Istituto di Servizi per il Mercato Agricolo Alimentare is taken into account. From the present study, it emerges that, while the average monthly temperature has little effect, it is a key determinant in lowering return variance (and hence the volatility).

1. Introduction

According to the vast majority of scientific studies conducted in the field of climate, global temperatures are rising. This conclusion is supported by empirical data from a variety of sources, including ground-based weather stations, satellite measurements, and ocean observations. Numerous studies and reports conducted by international scientific institutions, such as the Intergovernmental Panel on Climate Change (IPCC), the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the European Space Agency (ESA), have confirmed this trend of rising global temperatures. These researches found a net warming of the planet during the 20th century and continues to show an increase in global average temperatures over the 21st century. The data indicate that warming has occurred at a faster rate than would have occurred naturally without the influence of human activities, such as the emission of greenhouse gases from the burning of fossil fuels, deforestation, and other industrial activities. In particular, in recent decades, there has been a steady increase in global average temperatures. According to data from the Intergovernmental Panel on Climate Change (IPCC) report, the period between 1983 and 2012 was the warmest in the last 1.400 years globally. This increase in global temperatures has significant consequences for the environment, with impacts on sea level, biodiversity, marine and terrestrial ecosystems, weather patterns, and climate regimes. The oceans have warmed significantly, with consequences for marine ecosystems and sea level. Extreme weather phenomena such as heatwaves, storms and heavy rainfall have been observed to accentuate, which have a significant impact on human communities and the environment (Hochman *et al.* 2020). In addition, global warming has direct impacts on human society, affecting agriculture, water availability, public health (particularly for the most vulnerable elements of society), infrastructure, and the economy. In Italy, there has been an increase in average temperatures in recent decades (Iglesias *et al.* 2011; Linares *et al.* 2020). According to data from the "Servizio Meteorologico dell'Aeronautica Militare Italiana", between 1961 and 2019 the average annual temperature increased by about 1.25°C. Particularly in the last ten years, the Mediterranean region has become increasingly vulnerable to continuous climate change (Caccamo and Magazù 2019, 2021, 2023). According to Lionello *et al.* (2014), the increase in average temperatures in the Mediterranean region, together with a significant decrease in rainfall can be problematic for human economic and agricultural activities because it can lead to repeated periods of drought. Giorgi and Lionello (2008) carried out studies that show an increase in temperature in all seasons and for all parts of the Mediterranean region with good inter-model agreement. On the other hand, Mediterranean will be facing precipitation decrease especially in summer. Dubrovský *et al.* 2014, on the basis of 16 Global Climate Models, confirmed these results by analyzing future climate conditions for the Mediterranean region. Even over short distances, the spatial fluctuation of precipitation and temperature can alter the equilibrium of habitats, changing the behavior of many plant and animal species. At the last UN Climate Conference COP26 (November 2021), 197 countries adopted the Glasgow Climate Pact, setting +1.5°C as the target to keep the average temperature below the critical threshold. By keeping global warming below 1.5°C rather than below 2°C, certain dangers might be greatly mitigated and there would be a better chance for ecosystems and people to adapt to the changing climate. Unchecked climate change would have detrimental effects for Europe. Addressing the challenge of climate change is crucial to protect human health, preserve the environment, promote sustainable development, ensure social fairness, and promote global security. It is a complex task that requires globally coordinated actions and the participation of all sectors of society. The assessment of climate impacts and the development of strategies and plans for adapting to such changes may require knowledge of past and present climatic variations as well as an estimate of future observations. Several studies that measure across very wide geographic domains have been carried out to find the presence of substantial trends for certain meteorological variables. As regards Sicily, in particular, because of the broad orographic disparities between the northern portion, which is mainly mountainous, the eastern region, which is mostly volcanic, the south-eastern area that is mainly a plateau, the central-southern and south-western parts, which are mostly hilly, and the volcanic eastern area of the Sicilian region, there will inevitably be climatic variability. In the field of time-frequency characterization of meteorological data, Caccamo *et al.* (2016) demonstrated the effectiveness of wavelet transform in analyzing correlations between temperature, rainfall, and solar radiation, providing a valuable model for optimizing energy collection technologies. This approach can be extended to assess climatic variables and their impact on various sectors, such as agriculture. For this purpose, according to numerous researches it is important to delineate climatic zones with similar characteristics. In particular, Monforte and Ragusa 2022 carried out a study based on the Ward's cluster analysis method (Ward 1963) in which they calculated the monthly average temperatures using the data of the stations belonging to the respective cluster (Kaufman and Rousseeuw 1990). The temperature variability was investigated over a period of 90 years (1925-2015) and the Mann-Kendall test (MKT) and the non-parametric approach of Sens's slope were applied to quantify the significance of trends in time series and to evaluate the variation in trends. Overall, the data indicate a strong tendency of rising temperatures. The wintertime temperature rise that has been observed is unanticipated and concerning. There may be a loss of crops and plants due to the wintertime temperature increase, which is caused by climate change rather than territorial issues. The winter season's temperature increase would cause changes in the vegetative rest if the trends' developing monotonous character stays the same. This would have a major impact on the island's current process of desertification. Furthermore, increasing trends with a notable rate of increase occur in the spring, which has a detrimental effect on soil conditions, with a direct impact of the agricultural production translating into an increase of prices. The tendency for temperatures to rise over the summer, which exacerbates the drought phenomena, is significant but predictable. The season with the lowest rate of variation is the fall one, even if it is still growing. Sicily, the largest island in the Mediterranean, has a very variable climate, which is demonstrated in this research using a hierarchical aggregation method. Hierarchical cluster analysis is a method of cluster analysis widely improved in the field of Machine Learning to classify cases into groups that are relatively homogeneous within themselves and heterogeneous between each other. Homogeneity and heterogeneity are measured on the basis of a defined set of variables. It is possible to distinguish hierarchical clustering procedures in agglomerative and divisive. In the former, each of the n observations constitutes a separate cluster so that in the first step the two clusters that are more similar according to the same distance rule are aggregated. In the second step, another cluster is formed by nesting the two clusters that are more similar and so one. The procedure stops when all observations end un in a single cluster. In the divisive approach, all observations are initially assumed to belong to a single cluster, the most dissimilar one is extracted to form a separate cluster and so on until the final step will produce as many clusters as the number of observations. The results of a hierarchical clustering techniques can be visualized using a dendrogram, as reported in (Figure 1).

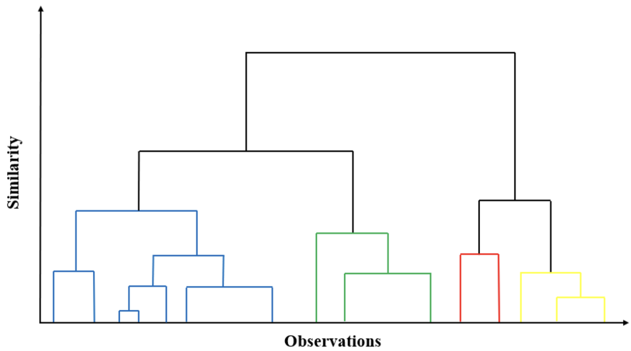


FIGURE 1. Example of a dendrogram with 4 clusters.

Climate variability can result in notable variations even for tiny areas of the country and can be influenced by various factors, including orography, closeness to the coast, and elevation above sea level. In Sicily, these alterations are intensified, leading to unusual rises in temperature. In fact, Monforte and Ragusa 2022 have shown that much of the region in the winter season has suffered a rise in temperatures of 2.0°C from 1925 to 2015. Therefore, if this trend tends to remain constant or to suffer a worsening, serious damage is expected to the economy of the region which, for the most part, is based on the agricultural sector. It appears clear that, in order to save the region's agriculture industry and, by extension, its economy, mitigation and adaptation measures must be focused on the areas most vulnerable to the effects of climatic variability. The current literature has been devoting an increase effort in analysing the impact of climate change on the economy, especially by means of the so-called Integrated Assessment Models (see Hope, Anderson, and Wenman 1993, among others). However, the sensitivity of this class of models with respect to the chosen impulse function (Pretis *et al.* 2018), has shifted the attention of researches to empirical analysis concerning the impact of climate changes on socio-economic variables (see Dell, Jones, and Olken 2014, for an exhaustive review). Most of the current literature focuses on the impact climate change on critical infrastructure: it is widely recognized that airports have been affected by climate change and extreme events in a broad sense – as measured by the volcanic activity – with the main hazard represented by ash fall, which may cause temporary closures of some airports due to accumulation on airport runways (Guffanti *et al.* 2009; Wilson *et al.* 2012); furthermore, as regards the issue related to safety, a protocol to obtain data for judging risks for aircraft and health was proposed by (Gislason *et al.* 2011), while general implications for crisis management were discussed by (Alexander 2013). Due to data availability, in most of the analysis, the climate changes are measured via level of temperature and/or rainfall. Recently, the attention of researchers was devoted to the impact of climate changes on financial variables: for example, in line with studies conducted by the (European Commission 2010) and the (International Air Transport Association 2010), (Mazzocchi, Hansstein, and Ragona 2010) find evidence of a negative impact of volcanic ash on asset returns, which lasts only for few days. As regards the impact on the economic activity, while most of the articles are based on economic outcomes, such as the GDP

(Pretis *et al.* 2018) or productivity (Sterner 2015), the branch of the literature focusing on the effects of climate change on agricultural sector is still narrow. In this paper, we fill this gap in the current literature by analyzing the impact of temperature and rainfall on the agricultural production. Due to data availability, we base our analysis on agricultural prices time series; however, given the well-known inverse relationship between price and the available quantity of goods and services, our results should also hold when the agricultural production is considered as the dependent variable. Importantly, given the Efficient Market Hypothesis (EMH) – according to witch all the public information is immediately absorbed by the market with an instantaneous adjustment of prices – it would not be possible to predict the impact of exogenous variable on price changes. For this reason, within this paper we aim to capture the impact of temperature and rainfall on the *probability* of observing a positive return between two consecutive observations. The empirical application, which is based on the price series of lemon produced in the city of Messina, reveals some interesting findings: firstly, the probability of observing a price increment is negatively related to the level of rainfall, while the level of temperature is statistically not significant; furthermore, in the analysis concerning the variation of prices, we find that the price remain more "stable" when the level of rainfall increases, while the risk of price changes increases when the level of temperature is higher.

The paper is structured as follows: Section **2** defines the models employed in the empirical analysis; Section **3** introduces the employed data set, while Section **4** is devoted to the discussion of the estimation results, with the relationship between climate change and variance of prices discussed in Section **4.1**. Finally, Section **5** concludes the paper with some remarks.

2. The model

The impact of climate change on the agricultural section is receiving an increasing attention both from investors and policy makers. Given the Efficient Market Hypothesis (EMH), in its strongest form, it would not be possible to predict the impact of exogenous variable on price changes; however, through suitable time series models, it would be possible to capture the impact of climate changes, as measured as the level of temperature and rainfall, on the *probability* of observing a positive return between two consecutive observations (see,among others Breen, Glosten, and Jagannathan 1989; Hong and Chung 2003; Christoffersen and Diebold 2006).

More in detail, basing on a time series of prices, the variable of interest in our analysis is a dummy variable taking value of 1 if the price at time t (p_t) is higher than the prevailing price recorded at time $t-1$ (it is equivalent to a positive return, *i.e.* $\frac{p_t - p_{t-1}}{p_{t-1}} > 0$). By considering the time series of the returns r_t, we define a latent variable y_t such that

$$y_t = \begin{cases} 1 & if \quad r_t^\star > 0 \quad \forall t = 2, \ldots, T \\ 0 & if \quad r_t^\star \leq 0 \quad \forall t = 2, \ldots, T. \end{cases} \tag{1}$$

As a consequence, the variable of interest is not a quantitative one but an indicator about the occurrence of a certain event. In other words, we work with a binary variable, which is generally modeled by means of the so-called *binary response model*. In such a setting, let

P_t be the probability that $y_t = 1$ conditional to the information set Ω_{t-1}, which contains exogenous, or independent, variables(temperatures and rainfalls, in our empirical application). In math terms,

$$P_t = Pr(y_t = 1|\Omega_{t-1}) = E(y_t|\Omega_{t-1}). \tag{2}$$

which should be constrained in order to be between 0 and 1, *i.e.*

$$0 < E(y_t|\Omega_{t-1}) < 1. \tag{3}$$

For this purpose, we need to use a proper functional form,

$$P_t \equiv E(y_t|\Omega_{t-1}) = F(z),$$

where $z = x_t'\theta$, with x_t' representing a specific row of the matrix of regressors, while θ is the set of parameters. Despite the relation expressed by $x_t'\theta$ is linear, it is not possible to estimate the model for $E(y_t|\Omega_{t-1})$ using the linear probability model, due to its incapability of observing the restriction stated in Eq. 3. Therefore, we adopt a functional form $F(\cdot)$ which is a transformation function ensuring the conditions usually used in the definitions of the cumulative density function (CDF), that is

$$F(-\infty) = 0, \qquad F(\infty) = 1, \qquad f(z) \equiv \frac{dF(z)}{dz} > 0.$$

In this setting, basing on the selected CDF, it is possible to derive the main binary response models, namely the *Probit* and *Logit* model. When the CDF is the one of the standard normal distribution is selected, *i.e.*

$$\Phi(z) = \frac{1}{2\pi}\int_{-\infty}^{z}(Z^2/2)dZ,$$

the so-called Probit model is obtained. Conversely, by adopting the standard logistic distribution

$$\Lambda(z) = \frac{e^z}{1+e^z},$$

we obtain the Logit model.

In both cases, the model is based on the following simple regression for $E(y_t|\Omega_{t-1})$

$$E(y_t|\Omega_{t-1}) = F(\delta_0 + \delta_1 temeperature_{t-1} + \delta_2 rainfall_{t-1} + \delta_3 y_{t-1}), \tag{4}$$

which – assuming $F(\cdot) = \Phi(\cdot)$ – corresponds to the *Dynamic Probit* model developed by Kauppi and Saikkonen 2008, where δ_0 is a constant, while *temperature* and *rainfall* are the lagged average level of temperature (in Celsius degrees) and rainfall (in millimeters); finally, y_{t-1} is the lagged value of the dependent variable, which should account for possible autocorrelation in the series (with $|\delta_3| < 1$ to ensure stationarity and invertibility of the model, Kauppi and Saikkonen 2008).

Given the availability of the densities in a closed form, both the Probit and the Logit model can me estimated via Maximum Likelihood Estimator (MLE). This is an estimation method which returns the parameters value that maximizes the likelihood (*i.e.* the probability) that the process specified by the considered model produced the data that were actually observed. In such a context, we make the assumption that y_t is an independent and identical distributed (i.i.d.) random variable drawn from a Bernoulli distribution (which is a limited discrete random variable taking the value of 0 or 1).It derives that the likelihood is given by

$$Prob(Y_1 = y_i, \dots, Y_n = y_n) = \prod_{y_t=0} [1 - F(z)] + \prod_{y_t=1} F(z),$$

so that the log-likelihood corresponds to

$$\mathscr{L}(\beta, \mathbf{y}, \mathbf{X}) = \sum_{t=1}^{T} y_t logF(\mathbf{x_t'}\beta) + (1 - y_t) log(1 - F(\mathbf{x_t'}\beta)).$$

Finally, as shown by (De Jong and Woutersen 2011), under appropriate regularity conditions – such as the stationarity of the explanatory variables, among others – the usual large sample theory applies to the coefficient estimated via MLE: in detail, the employed estimator is *consistent* (it converges in probability to the true value of the parameter), *efficient* (roughly speaking, it has the minimum variance) and *asymptotically normal* (which allows us to apply the standard theory for hypothesis testing on the estimated coefficients).

It is well-known that climate changes represent a threat for the agricultural sector. The increasing level of temperatures, as well as the even longer period of drought, has an impact on the agricultural production, leading to (sometimes) abrupt price changes. For example, for the considered market, a reduction of the level of rainfall (which in the extreme case leads to a drought period) is expected to reduce the production and hence it is expected to be positive related to a probability of observing a price increment (in Eq. 4, we expect δ_2 to be lesser than zero, and similarly for δ_1). This would also imply that the considered variables would be negatively related to the variability of prices, as measured by their variance. For this reason, we investigate such a relationship by augmenting the Autoregressive Conditional Heteroskedasticity model (ARCH, Engle 1982) by considering the effect of lagged temperature and rainfall as exogenous variables. The proposed model consists of two equations, which model the conditional mean (for returns) and the conditional variance, respectively. In particular, the conditional variance process is estimated by considering the squared residuals obtained from the conditional mean process. It derives the need to identify the correct process for the conditional mean. For the considered series (see Section **3**), the correlogram of returns (Figure 2, panel a) is coherent with a data generating process (DGP) of an Autoregressive Moving Average model, ARMA (see G. E. P. Box and Jenkins 1976, for more details about the identification of the best ARMA model). In general, for such a process, both the ACFs and the PACFs quickly converges to zero: in our case, since the PACF shows significance correlations (outside the confidence interval) for the first two lags while in the ACF only the first lag is significant, it is likely that the appropriate model for returns is the ARMA(2,1): for this reason, in defining the ARMA-ARCH model (Eq. 5) we consider two lags for the AR component and 1 lag for what concerns the MA.

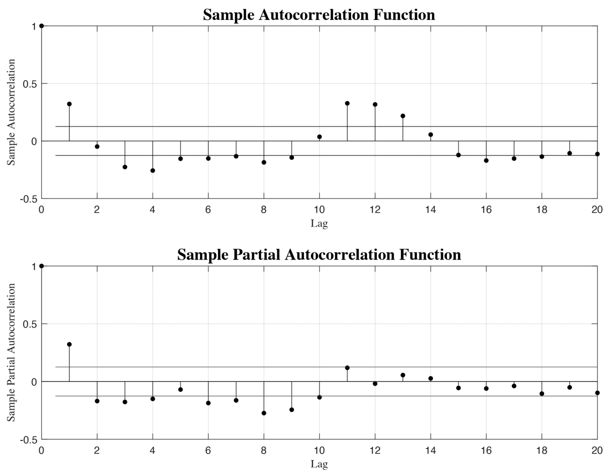
In particular, the model is defined as in Eq. 5,

$$\begin{array}{ll} r_t = \varphi_0 + \varphi_1 r_{t-1} + \varphi_2 r_{t-2} + \psi\varepsilon_{t-1} + \varepsilon_t & \varepsilon_t|\Omega t - 1 \sim N(0, h_t) \\ \varepsilon_t = h_t \eta_t & \eta_t|\Omega_{t-1} \sim N(0,1) \\ h_t = Var(\varepsilon_t) = \omega + \alpha\varepsilon_{t-1}^2 + \beta_1 temperature_{t-1} + \beta_2 rainfall_{t-1}, & \end{array} \tag{5}$$

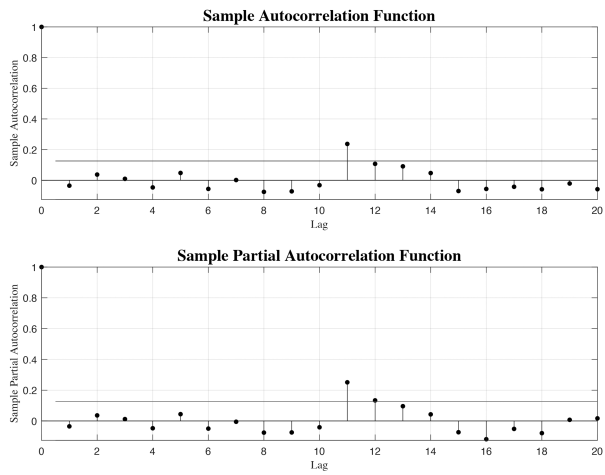
where the first and the third equations define the processes followed by the conditional mean and variance (h_t), respectively. The mean equation follows an ARMA(2,1) process, for which invertibility is ensured by the same condition for an invertible MA(1) process

($|\psi| < 1$), while stationarity conditions are those of the AR(2), *i.e.* φ_1 and φ_2 should be inside the triangular region:

$$\begin{aligned} \varphi_1 + \varphi_2 &< 1; \\ \varphi_2 - \varphi_1 &< 1; \\ -1 < \varphi_2 &< 1. \end{aligned}$$



(a) returns



(b) residuals

FIGURE 2. returns (a) and residuals (b) autocorrelogram.

As for the variance equation, it follows an ARCH(1) model with exogenous variables impacting the conditional variance through the coefficients β_1 and β_2, respectively. Importantly, the model might be extended by considering further lags of the squared residuals ε_{t-p}^2

($ARCH(p)$) or by including the lagged value of the conditional variance h_{t-1} (obtaining the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH, Bollerslev 1986) is obtained). However, both these generalizations requires a sample size of at least 500 observations, while a sample of 250 observations is enough to reduce the bias in the MLE of the ARCH(1) model. For this reason we opt for this specification (Hwang and Valls Pereira 2006), even if a more sophisticated one could be appropriate to capture the persistence feature characterizing the variance (or volatility) process.

3. The Data

We base the empirical analysis on the time series of the market price of lemons in Sicily, by taking the market of Messina as leading examples. Our dataset consists of 254 monthly observations from January 2002 to February 2023. The price series is provided by *Istituto di Servizi per il Mercato Agricolo Alimentare* (ISMEA)[1], while we get data on temperature and rainfall from the *TuTiempo* weather website.[2] Figure 3 shows the evolution of the price (top panel), average temperature (middle) and average rainfall (bottom), together with their sample autocorrelation function (ACF). The presence of a trend in the price time series emerges at a first sight: it is evident how the series does not fluctuate around its mean, rather it has an average value of 0.272 in the period 2002–2008, increasing to 0.373 in the period 2009–2015 and reaching the level of 0.653 for the last sub-period 2016–2023 (see Table 1); conversely, both the temperature and the level of rainfall do not show any trend, but they are clearly affected by seasonality (defined as regular and predictable changes that are related to calendar time), which emerges looking at the regular peaks affecting both the time series and the ACFs: in detail, the peaks observed at lag 12 are coherent with an annual seasonal behavior of the series. In order to avoid spurious correlations among the variable, we base the empirical analysis on deseasonalized series, which are obtained by applying the *Stable Seasonal Filter* in Matlab. As shown in Figure 4, both the temperature and rainfall time series no longer show sign of seasonality, with sample autocorrelations lying within the 5% confidence interval. Conversely, the ACF of the deseasonalized price series is still the one of a persistent series but this will not affect the empirical analysis since the trend is successfully removed when computing the monthly returns.

TABLE 1. Price, temperature and rainfall sample mean.

	2002–2008	2009–2015	2016–2023	2002–2023
Price	0.2722	0.3734	0.6526	0.4345
Temperature	19.1492	18.8769	19.1145	19.0474
Rainfall	2.8922	2.9439	2.4289	2.7524

[1]The price time series is available at https://www.ismeamercati.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/5391.

[2]Data can be manually downloaded at https://it.tutiempo.net/.

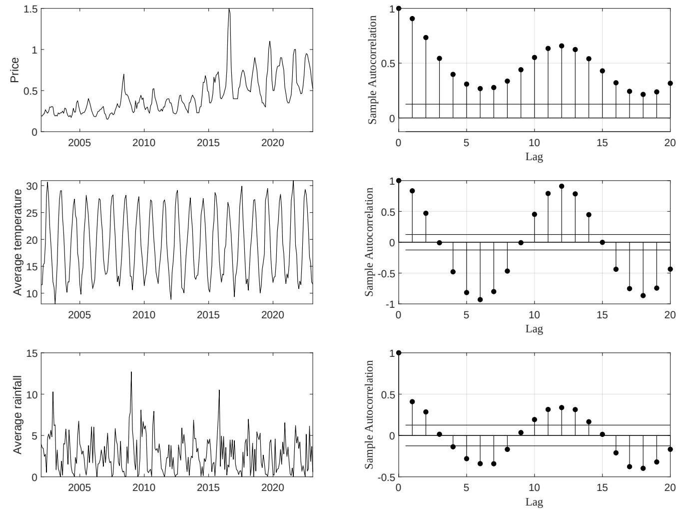


FIGURE 3. Price (top), average temperature (middle) and average rainfall (bottom) time series and ACF. Sample period: January 2002 – February 2023.

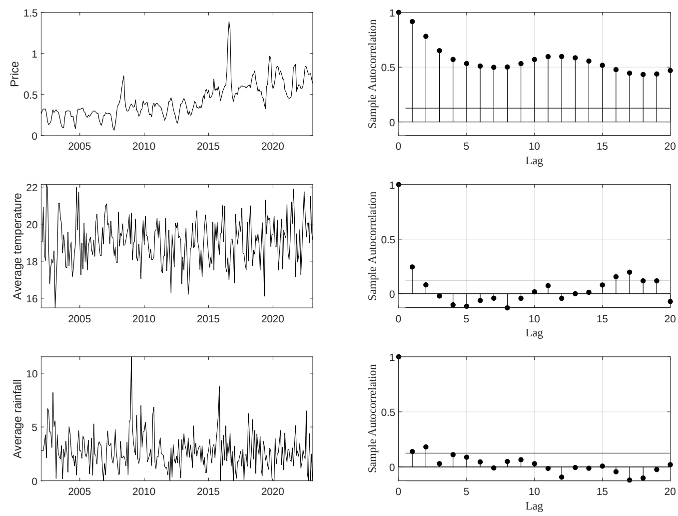


FIGURE 4. Price (top), average temperature (middle) and average rainfall (bottom) time series and ACF of deseasonalized series obtained via *Seasonal Stable Filter.*

4. Estimation Results

Being agnostic about the distribution (normal rather than the logistic), in what follows we discuss results based on both Probit and Logit models. As shown in Table 2, not surprisingly, the coefficient related to the temperature is not significant since it has a deseasonal average of about 22 degree Celsius, which is ideal for the production of lemon. As expected, the rainfall enters the model with the expected negative sign, with an increase in rainfall being associated with a lower probability of observing a price increment (positive return) in the next month. Finally, the ψ coefficient is positive, pointing out to a positive relationship between the expected probability and its own lagged variable.

The same table reports the marginal effects, which measure the impact of a marginal increase of a variable (with all the others remaining constant) on the estimated price increment probability. Focusing on the marginal effects of *rainfall*, on average it reduces the price increment probability by 3.6%.

Finally, the last row of Table 2 shows the rate of success, *i.e.* the percentage number of cases in which our predictions coincide with the dependent variable (y_t). For this purpose, a new dummy variable taking value of 1 if $\Phi(\mathbf{x}_t'\hat{\theta}) > 0.5$ with $\hat{\theta} = [\hat{\alpha}\ \hat{\beta}\ \hat{\delta}\ \hat{\psi}]$ is created. In conclusion, for both the models, we have a rate of success well above 60%, with a maximum of 62% obtained with the Probit model, meaning that we successfully predicted the increment of price in 6 out of 10 cases.

TABLE 2. Probit and Logit estimated coefficients and marginal effects (robust standard errors in parentheses). Level of significance: (⋆) 1%; (⋆⋆) 5%; (⋆⋆⋆) 10%. Sample period: January 2002 – February 2023.

	Probit		Logit	
	Est. Coeff.	Marg. Effects	Est. Coeff.	Marg. Effects
δ_0	0.7964		1.3056	
	(1.3697)		(2.2237)	
δ_1	−0.0403	−0.0161	−0.0660	−0.0165
	(0.0697)	(0.0278)	(0.1131)	(0.0282)
δ_2	−0.0893⋆	−0.0356⋆	−0.1442⋆	−0.0360⋆
	(0.0490)	(0.0195)	(0.0790)	(0.0197)
δ_3	0.5167⋆⋆⋆	0.2028⋆⋆⋆	0.8308⋆⋆⋆	0.2073⋆⋆⋆
	(0.1612)	(0.0642)	(0.2608)	(0.0651)
Rate of success	62.30%		61.90%	

4.1. Climate change and variance of agricultural price. Results discussed in Section **4** point out to a inverse relationship between the level of rainfall (and temperature) and the probability of observing a positive return in the considered market. Such a relationship would imply that the fluctuations of the return series around its mean would be less pronounced when a higher temperature (or a higher level of rainfall) are recorded. In economic terms it translates into a negative relationship between temperature (or rainfall) and volatility (*i.e.* the square root of the conditional variance of returns). We investigate such a relationship by augmenting means of an ARMA-ARCH model with exogenous variables (c.f. Eq. 5).

Estimation results, obtained via MLE, are shown in Table 3. As regards the mean equation, coefficients are highly significant at a 1% level and they are coherent with a stationary and invertible process; furthermore, the process seems to be appropriate for the considered time series, since the regression residuals are i.i.d, as emerged from the correlogram shown in panel b of Figure 2. This is also confirmed by the p-value of the of the Ljung-Box (Ljung and G. E. Box 1978) statistics, reported in the bottom of the same table. It is a statistical test used to verify the null hypothesis that residuals are independently distributed. Fail to reject this hypothesis is crucial in modelling time series: having not independent (or even correlated) residuals is a sign of mis-specification of the model. In most of the cases, residual auto-correlation arises due to the omitted variable problem. If some exogenous variables – that are important to explain the variability of the dependent variable – are omitted, their impact is captured by the residual term, which turns out to be dependent from its past values. In our empirical application.

As for the variance process, the estimated coefficients are statistically significant at a 1% level, with a persistence of 0.74 as estimated by the coefficient α. As largely expected, both the temperature and the rainfall enter the model with a negative sign, having a negative impact on the conditional variance. This can be interpreted as evidence for our intuition that the fluctuations of the returns series around its mean would be less pronounced when a higher temperature (or a higher level of rainfall) are recorded. Even for the variance equation, we always fail to reject the null hypothesis of no autocorellated residuals, since the p-value is well-above the reference value of 10% for all the considered lags. In other words, even if we are considering the simplest ARCH specification, the model is well specified and it is sufficient to capture the autoregressive nature of the conditional variance. In conclusion, even though the average monthly temperature does not impact the probability, it is an important determinant in reducing the variance (and hence the volatility) of returns.

Figure 5 compares the evolution of the estimated conditional variance h_t (red line) and one of its natural proxy ε_t^2. Even though we are not properly considering volatility (the square root of the conditional variance), both the series show the well-known volatility clustering phenomenon, which implies that periods of low volatility tend to be followed by periods of low volatility, while periods of high volatility (when the series spikes) tend to be followed by periods of high volatility. As a matter of fact, the spikes in the variance series correspond to months when the level of rainfall is low. For example, the highest spike is observed on October 2004, when the level of rainfall was about 3.24mm, with a 500% increment with respect to the previous month: this result could be interpreted as evidence for the threat that climate change might represent for the agricultural sector in the region. According to the last Drought Report released by Regione Sicilia in December 2023, the last quarter of the year was characterized by a level of rainfall that was much lower than the average level of the last 30 years. This, together with the increasing level of temperature, would imply a higher volatility for the lemon price which might translate in a lower demand and, as a consequence, lower profit for agricultural firms.

TABLE 3. ARMA-ARCH estimated coefficients (robust standard errors in parentheses, White 1980) and the p-value of the Ljung-Box statistics. Level of significance: ($\star$) 1%; ($\star\star$) 5%; ($\star\star\star$) 10%. Sample period: January 2002 – February 2023.

Mean equation		Variance equation	
φ_0	0.0012	ω	0.0901***
	(0.0008)		(0.0308)
φ_1	1.1675***	α	0.7421***
	(0.0588)		(0.2068)
φ_2	$-0.4831^{\star\star\star}$	β_1	$-0.0038^{\star\star}$
	(0.0584)		(0.0015)
ψ	$-0.9442^{\star\star\star}$	β_2	$-0.0009^{\star\star\star}$
	(0.0273)		(0.0003)
	Lag 1	0.5748	0.8707
	Lag 5	0.8692	0.5154
	Lag 10	0.8294	0.5785

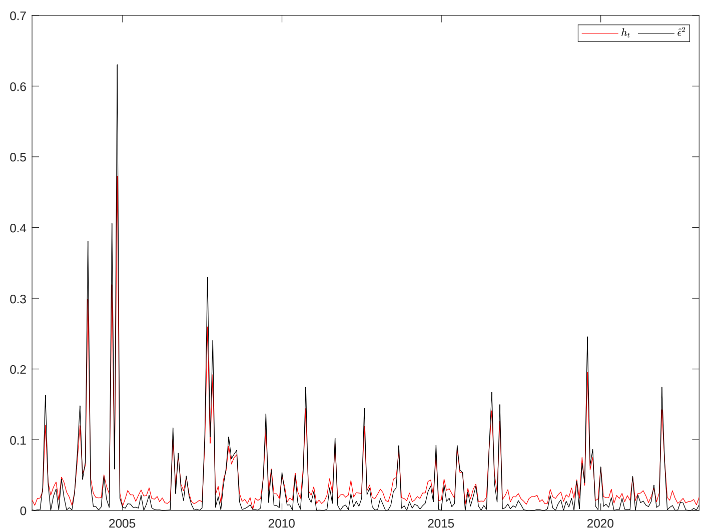


FIGURE 5. ε^2 (black line) and the estimated conditional variance h_t, (red line).

5. Conclusion

In this paper, we deep insight the branch of the literature concerning the impact of climate changes, measured by the average level of temperature and rainfall, o the economy. We focus on the regional agricultural sector, by analysing the prevailing price of the lemon market in the city of Messina. Given the unpredictability of prices and returns (due to the Efficient Market Hypothesis, EMH), we rather analyse the impact of climate changes on the probability of observing a positive returns (measured with a dummy variable taking value of 1 if the first difference of prices is positive, and 0 otherwise) and on the variability of the returns themselves. The empirical application reveals some interesting results. Via both a logit and probit model, we find that the modelled probability responds only on the average level of rainfall: the estimated coefficients is negative, with a marginal increase in rainfall leading to a 3.6% reduction of the probability of observing a price increment. Furthermore, by means of a ARMA-ARCH model, we find that both temperatures and rainfalls reduces the variability of returns, as measured by the conditional variance. This result can be interpreted as evidence for the intuition that returns (and hence prices) remain stable, fluctuating around their mean value, when temperature and rainfall are higher. In conclusion, the empirical analysis confirms the existing relationship between climate changes and the agricultural sectors: the even longer (and frequent) periods of drought, together with the increasing level of temperature, experienced in the last years, might represent a risk for the regional production, leading to higher price and lower demand, with a direct impact for the profit of agricultural firms, as a consequence.

This analysis may be considered as a starting point for future researches. For example, with a longer sample period, it would be possible to enrich the dynamics of the conditional variance equation by estimating a GARCH model and investigate whether our results are robust with respect to the inclusion of an autoregressive term. Furthermore, given the proper characteristics of the Sicilian economy, which highly relies on the primary sector, for a local policy maker it could be interesting to analyze the impact of climate changes on the Sicilian business cycle, *i.e.* cyclical upswings (also known as expansions) and downswings (recessions, defined as at least 2 quarters of negative GDP growth) in a broad measure of economic activity, the gross domestic product (GDP). For example, by augmenting the Markov switching (MS) autoregressive model (Hamilton 1989) it would be possible to characterize the different phases of the regional business cycle, each of which corresponding to a non-observable regime, with probabilities depending directing on some observable variables related to climate change

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